Identifying Relevant Information for Emergency Services from Twitter in Response to Natural Disaster

Avijit Paul
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Creative Industries Faculty
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Emergency services, Twitter, Social Media, Computational Social Science, Big data, Natural Language Processing

Abstract

During recent natural disasters (e.g., Queensland Flood in 2010-2011 and Earthquake, Tsunami and Nuclear Crisis in Japan 2011, Typhoon Haiyan in 2013) millions of status updates appeared on various social networks. This suggests that people's reliance on social media at times of disaster has increased tremendously in recent years. However, the greatest concern to emergency services when it comes to harvesting information from users of social media is the quality of the received data content. At present it is highly problematic to differentiate between information that has a high degree of disaster relevance and that information which has a very low degree of disaster relevance. And this is not simply an inconvenience, it poses a significant challenge that if resolved can mean the difference between life-saving decisions and life-wasting decisions.

This project analyses natural disaster related conversation in Twitter that occurs during the dynamic states of an unfolding disaster. It proposes a framework that identifies high-value disaster based information by digitally harvesting and categorising social media conversation streams that are relevant for emergency services for intelligence gathering and to facilitate key decision-making processes during times of natural disaster. The original contribution of this thesis is three-fold. The first contribution is in the creation of a new coding category that emergency services and researchers in crisis communications can use when analysing contents relating to natural disasters. The second contribution is the framework that combines novel features using well-established algorithms to identify disaster relevant conversations from social media streams. Methods for extending qualitative analysis to large scale quantitative analysis in the area of social media and Twitter research is the third contribution of this research.

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Publications

Woodford, D., Walker, S., & Paul, A. (2013). Slicing Big Data: Extracting important information from a social network stream during crisis. In Selected Papers of Internet Research 14.0 (pp. 10-13). Denver, USA: AOIR.

Paul, A (2013, May 28 - 30) *A framework for identifying named entities from social media discussions in crisis situation*, Paper presented in Australian and New Zealand Disaster and Emergency Management Conference, Brisbane, Australia.

Paul, A & Bruns, A (2013) Usability of small crisis data sets in the absence of big data. *In Ariwa, Ezendu, Zhao, Wenbing, & Gandhi, Meenakshi (Eds.) Proceedings of the 2013 International Conference on Information, Business and Education Technology*, (pp. 718-721) Beijing, China Atlantis Press.

Statement of Original Authorship

The work contained in this thesis has not been previously submitted to meet requirements for an award at this or any other higher education institution. To the best of my knowledge and belief, the thesis contains no material previously published or written by another person except where due reference is made.

QUT Verified Signature

Signature:

Date: October 2015

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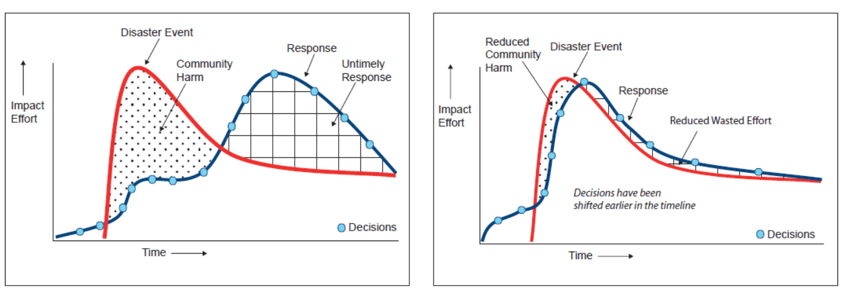
Chapter 1: Introduction

The first 24 hours is considered the most crucial time in a natural disaster and is when most community harm occurs (Queensland Government, 2012a). Delays in attaining actionable information following a natural disaster have been shown to lead to an increase in the number of casualties and to a slow response time from disaster responders (Meier, 2012). Varying the range of sources used to identify information relevant to disaster management to include social networks, for example Twitter, has the potential to decrease the time it takes to find this information, to minimise response time and to help to reduce community harm (McElroy, 2014; Platt, Hood, & Citrin, 2011b). Figure 1 shows a model of reducing community harm and the associated factors, including a timely and impactful response immediately following the disaster. This includes disaster management services obtaining immediate access to relevant information that can be actioned. As immediate updates of situations can be found in social media, this study investigates how disaster relevant information can be automatically identified from social media streams.



Current situation

Optimal situation

Figure 1: Current and optimal situation after natural disaster (Queensland Government, 2012a)

1.1 Context of the Study

A number of recent natural disasters, including the New Zealand earthquake (Christchurch, 2011), the Japanese tsunami (2011), Queensland flood (2012) and Typhoon Haiyan in the Philippines (2013) have framed social network sites as globally accepted channels for sharing information about disasters. The primary uses include providing updates on specific situations, requests for help, as well as general well-wishes and expressions of concern. The use of social media for this purpose has positioned it as a significant and powerful information source during crisis events (Muralidharan, Rasmussen, Patterson, & Shin, 2011). According to the American Red Cross (2011), people who use social media to share information about disasters expect emergency response organisations to monitor and respond to what they share (American Red Cross, 2011).

During recent natural disaster events (e.g., Queensland flood, Japanese earthquake) the social networking sites Facebook and Twitter were the most utilised sites for both sharing and accessing news and updates on the unfolding events. Research shows that due to the 'walled garden' approach Facebook has become less accessible than Twitter for public communication (Bruns, 2012). Given Twitter updates are publicly available to non-registered users, it is a platform that allows any user to follow any other user without knowing them personally. Ability to follow any user on Twitter allows community members to monitor communication from a crisis authority organisation (e.g., Department of Community Safety, Queensland Government) during a disaster in order to get real time updates. This frames Twitter as a unique platform that simultaneously collects and stores a large pool of potentially life saving disaster related information and that acts as a key dissemination channel and information source at the same time. For this reason Twitter was selected as the social networking site to be investigated within this research project for its potential to provide timely critical information to emergency services.

Keeping track of the rapid flow of Twitter updates in order to filter useful information is a key issue impacting tracking disaster communication (McElroy, 2014). Current research on Twitter uses the method of following hashtags and keywords to identify messages related to a specific natural disaster in order to retrieve disaster relevant information (Garcia-Herranz, Egido, Cebrian, Christakis, & Fowler, 2012; Potts, Seitzinger, Jones, & Harrison, 2011; Tsur & Rappoport, 2012). However these methods of tracking information via hashtags and keywords have limitations. A dominant hashtag can produce thousands of tweets per second (Empson, 2012; Mandel et al., 2012) making the task of manually monitoring the information flow humanly impossible. This is because the task of emergency services is not limited to identify that a disaster is in progress, but to find out which of the tweets have actionable information (e.g., reports of flooding roads with location indicated) and which are personal narratives (e.g., well-wishers or expressions of community concern).

Researchers have made numerous attempts to devise tools for automated Twitter analysis by using machine learning algorithms to identify potentially relevant tweets (Bruns & Stieglitz, 2012; Lau, Tao, Tjondronegoro, & Li, 2012; Verma et al., 2011; Acar & Muraki, 2011; Banerjee, Chakraborty, Joshi, Mittal, Rai, & Ravindran, 2012; Culotta, 2010; Hughes & Palen, 2009; Rogstadius, Vukovic, Teixeira, Kostakos,Karapanos & Laredo, 2013). Chapter 2 and 3 discusses this in more details.

However, to date the process of using human intelligence has outperformed automated systems in determining whether a tweet is disaster relevant and actionable by disaster response units. As emergency services have limited human resources, dedicating these to the evaluation of social media feeds in order to identify disaster relevant information is not practical and does not take priority over their core roles and responsibilities during and after a natural disaster. This research presents a potential for new approaches in presenting Twitter information to emergency services.

This study focuses on developing and testing a set of new approaches to produce a subset of updates that is likely to be disaster relevant and actionable by disaster management and to enable them to harness social media more effectively. To do that, this research project analyses the needs of emergency services after a natural disaster and then formulates a framework to identify disaster relevant information for emergency services. Based on the identified information needs, the study further develops a theoretical framework for new methods of automatically identifying disaster relevant information from social media and tests it using data sets of Tweets from two recent disasters. By building a theoretical framework for a new approach to identifying disaster relevant information and an automated system to test it, this project reframes the flow of social media content from conversation streams to targeted actionable information that can help emergency services make life saving decisions.

1.2 Aim and Scope

The main aim of the study is to help emergency services to identify natural disaster relevant information on social media using individual user tweets and updates. The automated filtering approach will assist emergency services with the evaluation of Twitter messages by eliminating the unsustainable process of manually monitoring thousands of tweets after a natural disaster, to instead focus evaluation efforts on a handful of targeted messages with the highest degree of relevance. The aim of the study is therefore not to focus on filtering out irrelevant social media updates. Instead the research aims to develop a method that mimics a manual human evaluation process using a set of automated techniques that reduce the unmanageable number of tweets to a small enough sample that can be readily assessed by the emergency services for critical actionable information.

It is outside the scope of this study to create an automated way of identifying if a natural disaster has occurred. The scope of this study is further limited to disaster information requirements of emergency services such as Department of

Community Safety, Red Cross or similar humanitarian organisations. As the scope of this study is limited to natural disaster, man made disasters including terrorism and sabotage is not included in this dissertation. In addition, General tweets found not to be relevant for emergency services are not included in this research. Thus, the research questions focus on identifying what is specifically relevant for emergency services in a disaster rather than what might be generally relevant. It is also necessary to address that as this thesis focuses on getting information from social media, density of social media users is an important variable in information gathering from social media. If an area has a lower number of social media users, amount of information that can be gathered from there even in the case of severe situation is potentially lower than in an area with high number of social media users.

A minimum social media literary is also needed by a user to be able to contribute in social media stream. This would involve having a social media account or being able to create an account. For the purpose of using Twitter during crisis this will also include ability to use a hashtag to engage in an existing discussion about crisis. In addition, having a mobile device from where the user can tweet also assist in producing content during crisis event.

1.3 Research Question

This thesis has a central research question, which is further divided into two sub-questions. Dividing the central research question in two parts allows first part of the research to focus on identifying information needs from emergency services and in the second part to focus on automatically finding the type of information identified as relevant in the first research question.

Central Research Question: How can relevant information for emergency services be identified from social media streams automatically in response to natural disaster?

During a natural disaster and immediately afterwards Twitter updates are posted at a rapid pace, which further emphasises the need for emergency services to identify relevant and potentially actionable information. Even though it is possible to read through real time social media data, the large volume makes it a difficult task. Navigating through thousands of Twitter updates to identify those containing actionable information remains a major challenge for emergency services. Therefore, a key aim of this research is to develop and test a new procedure that automates the process of manually identifying relevant information for emergency services and enables an emergency response to be actioned.

Sub Research Question 1: What is relevant information for emergency services during and following a natural disaster?

As relevant is a relative term, the first problem to address is to determine what constitutes relevant information for emergency services during and after a crisis situation. Although there are various metrics currently available from social media research, the question remains if these metrics contain the same type of information emergency services are looking for, and if not, what is instead considered relevant by them.

Sub Research Question 2: How can this relevant information be identified automatically?

After identifying disaster relevant information, the next question is how can this information be identified automatically and can this method be used to identify relevant tweets from the sample of all available tweets on the topic. In order to do that, the data is first analysed manually to determine how a human evaluator selects and evaluates an individual message as disaster relevant. Secondly, once the new automated process is developed, it is tested on the same data set to determine how closely the automated evaluation results mimic the manual process of human evaluation undertaken in the first step.

1.4 Significance of the Study

This research proposes a novel contribution to identify disaster relevant information from Twitter for emergency services. In order to improve identification of disaster relevant information from Twitter, it extracts four features from tweets and combines them to assign a disaster relevance score. By using this relevance scoring algorithm emergency services can rank tweets according to their relevance and exclude tweets below a certain threshold score to reduce the amount of incoming tweets they need to review to find relevant information from social media.

The contribution of this research also includes the proposal of a new coding category to identify disaster relevant tweets. This coding category can be used by other researchers and emergency services to categorise incoming tweets based on their relevance, qualitatively or quantitatively. By combining existing coding categories with information needs for emergency services, this coding category advances the grouping of disaster relevant information beyond the currently available categories.

The iterative research process used in this project also extends existing interdisciplinary approaches in Twitter research. The method of using both manual and automated analysis that was applied in this research can be used by other researchers in the field of social media. Evaluating outputs from algorithms with crowdcoded evaluation is a novel evaluation approach that has not previously been used in the context of social media in disaster research and can be adopted by other researchers.

1.5 Thesis Outline

This dissertation consists of seven chapters in four main parts. The overall thesis outline is presented in Figure 2.

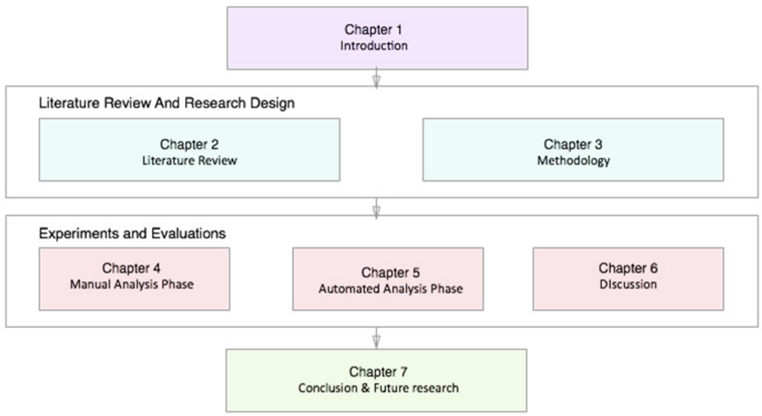


Figure 2: Thesis outline

In this Introduction (Chapter One) the overall position of this thesis, aim, scope and research question has been described. The discussion then focuses on reviewing literature, working documents and frameworks used by emergency services to find what is likely to be considered as relevant information for emergency services (Chapter Two). This is followed by a description of the research design and methodology (Chapter Three).

The second part of the research is built on the first part where a manual analysis was conducted on a small sample from two different datasets to identify the features that separate a relevant from an irrelevant tweet (Chapter Four). Following that an automated analysis was performed on the entire datasets to find out if these features can be identified automatically (Chapter Five).

This leads to the third part where the findings were combined to create the overall framework that is used to identify disaster relevant information automatically and evaluate the outcome to find out if it can really identify disaster relevant information (Chapter Six). In the conclusion (Chapter Seven) the findings from the combined framework and evaluation are summarised to describe if this research has achieved the aim and to suggest potential future research.

Chapter 2: Literature Review

The primary research aim of this thesis is to find relevant information for emergency services at times of natural disaster. This chapter therefore reviews academic literature related to emergency services management, natural disasters and information gathering from social media.

2.1 Research Domain and Literature Map

This dissertation falls in the broad spectrum of **Crisis Informatics**, an applied interdisciplinary research paradigm that integrates technical, social as well as informational facets of crisis events (Artman, Brynielsson, Johansson, & Trnka, 2011; Pipek, Palen, & Landgren, 2012; Shklovski, Burke, Kiesler, & Kraut, 2010). The literature review is constructed around the three disciplines of crisis informatics – disaster management, media and communication studies (including social media studies) and computer science (Figure 3).

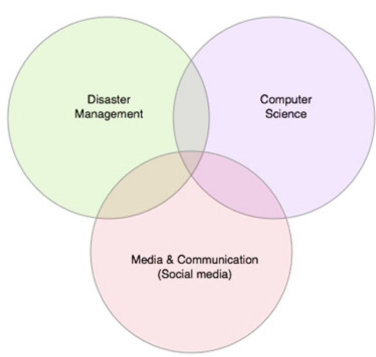


Figure 3: Research domain and concept map of the literatures reviewed

Disaster management The first component of Figure 3 is disaster management. This section discusses literature from the perspective of the disaster managers who are responsible for humanitarian aspects of emergencies. They are involved in all phases of disaster cycle in order to lessen the impact of disasters. What they deem as relevant information after natural disaster is addressed in this section.

Media and communication studies The second component of Figure 3 is literature related to media and communication, especially social media in everyday life and role of social media during and after natural disaster, focusing on Twitter. Key challenges of using Twitter in disaster situations are discussed in this section. This is followed by a discussion of the common elements between information needs of emergency services and what is available on Twitter.

Computer science The third component of Figure 3 is literature from computer science because crisis informatics uses technology for various phases of disaster. This section looks at various methods used in computer science to collect analyse and evaluate information automatically.

Of these three disciplinary areas of crisis informatics, first two are discussed in the literature review chapter and third, computer science, is discussed in the methodology chapter. This is not to suggest that computer science literature has been viewed only from a methodological point of view. Various computer science theories have been evaluated for this thesis. In addition some of the tools developed in this thesis also used computer science theories. Therefore it was positioned in the Methodology so that both theory and practical discussions can be included in the same area.

2.2 Hazard, Emergency and Disaster

This section provides an overview of the key theories and practices of disaster management, particularly those related to response phase of disaster management. As this thesis focuses on identifying relevant information from social media after a natural disaster, the aim of this section is to identify what emergency services need that can potentially be found in social media. Therefore the literature reviewed in this section mostly focuses on crisis communication.

Before proceeding, it is necessary to discuss the terminologies related to crisis and disaster, because there is a degree of uncertainty around the words used to describe natural disasters. Despite the common uses of the word 'crisis' and 'disaster' to suggest a catastrophe, emergency services use different terms to identify the severity of the event : hazard and emergency (Smith, 2013). Generally, when a situation affects many people and arises due to massive scale natural (e.g., earthquake, cyclone) or technological (e.g., structural failure, terrorism) events that exceed the ability of the emergency services (e.g., fire, ambulance, police), it is classified as disaster by emergency services (Haddow, Bullock, & Coppola, 2010).

Based on the emergency services definition, the smallest unit of a disaster situation is known as a 'hazard'; which stands for the source of danger that may or may not lead to emergency or disaster (National Governors Association, 1979). An 'emergency' is "a serious, unexpected, and often dangerous situation requiring immediate action" (McConnan, 1998) that can be relevant for an individual or for a community. In most cases if an emergency situation is life threatening, emergency personnel (e.g., fire brigade, police) are called into action.

The term 'disastrous' event on the other hand is reserved for something much bigger. Usually for an event to be considered disastrous it needs to affect one or more critical areas – shelter, fire suppression and mass care – and has to occur in a area too large for emergency services to handle. Therefore, from an emergency services point of view, a building fire is not a disaster, but a bush fire across a state is a disaster, as it suppresses their ability to control the fire.

However, literature can also refer this situation as a crisis situation (Liu, 2010; Palen & Liu, 2007; Reynolds, Galdo, & Sokler, 2002). As each of these terms can refer to a different degree of damage, this dissertation aims to use the appropriate terminology as based on the status of the situation

2.2.1 Types of natural disasters

In order to justify why the scope was limited to natural disasters, this section first discusses the differences between types of disasters, followed by natural disasters in historical context. Therefore before going deeper, it is necessary to clarify the scope of this thesis in terms of the hazards it discusses.

Historically early classification of hazards only included situations that were caused by natural forces, as it was difficult for people to create a disastrous situation affecting large group of people. However, in recent years it has become increasingly possible for a disaster to be man made. Therefore various organisations have created various types of classification. Among them, one of the most widely used classification was created by Centre for Research on the Epidemiology of Disasters (CRED) under World Health Organization (WHO) (Below, Wirtz, & Guha-Sapir, 2009) which classifies all hazards based on their source: natural and man-made. Since other emergency service organisations such as Red Cross and FEMA also follow this classification (Haddow, et al., 2010), it was used in this dissertation. Following are some of the example of natural and technological (man-made) hazards.

A) Natural hazards Hazards that are caused by natural forces are grouped under the category Natural Hazard. These can be caused by hydrological (flood), meteorological (cyclone, bushfire), seismic (earthquake), biological (epidemic), volcanic or other natural processes, and often affect a large community of people.

B) Technological hazard Technological hazards are often man made hazards that result from the failure of man made objects. Like natural hazards, man made or technological hazards can arise from various causes such as transportation failure (ship, plane), infrastructure (building, bridge) collapse, terrorism, sabotage and nuclear hazards.

The biggest difference between these hazard categories is that, excluding nuclear hazards, man made hazards often affect hundreds of people, while natural hazards commonly affect thousands and are often elevated to the status of disaster (Haddow, et al., 2010). Since this research focuses on disasters that affect many people, the scope was delimited to natural disasters.

2.2.2 Natural disaster classification

Hazard classification from CRED also includes further classification of natural disasters. Although there are many different types of natural disaster researchers from CRED classified in three major groups based on their trigger (Figure 4) (Below, Wirtz, & Guha-Sapir, 2009). They are:

- **Biological**: disasters caused by the exposure of living organisms to germs and toxic substances
- **Geophysical**: events originating from solid earth
- **Hydro-meteorological**: which is further divided into three parts:

    Hydrological: events caused by deviations in the normal water cycle and/or overflow of bodies of water caused by wind set-up
    Meteorological: events caused by short-lived/small to meso-scale atmospheric processes (in the spectrum from minutes to days)
    Climatological: events caused by long-lived/meso- to macro-scale processes (in the spectrum from intra-seasonal to multi-decadal climate variability)

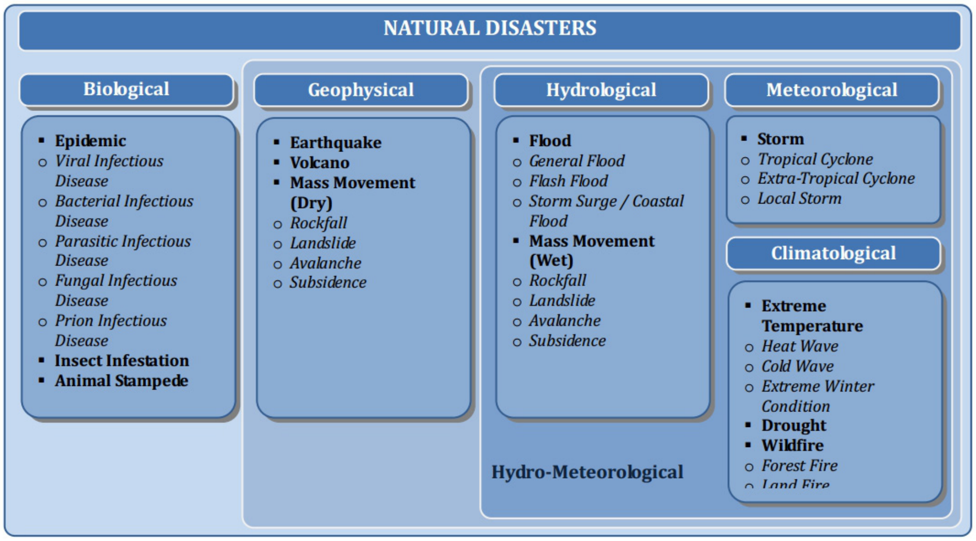


Figure 4: Natural Disaster Classification by Below et al. (2009)

2.2.3 Historical context

However not all natural disasters affect people equally. Historical context allows us to gain a better understanding about natural disasters and their affect. Although there have been earthquakes, flood and various other natural disasters for centuries, the damage caused by all natural disasters are not the same. Figure 5 shows estimated damage costs of natural disasters for over 100 years, and it can be seen that the most destruction in terms of damage cost were caused by tsunamis, hurricanes and earthquakes.

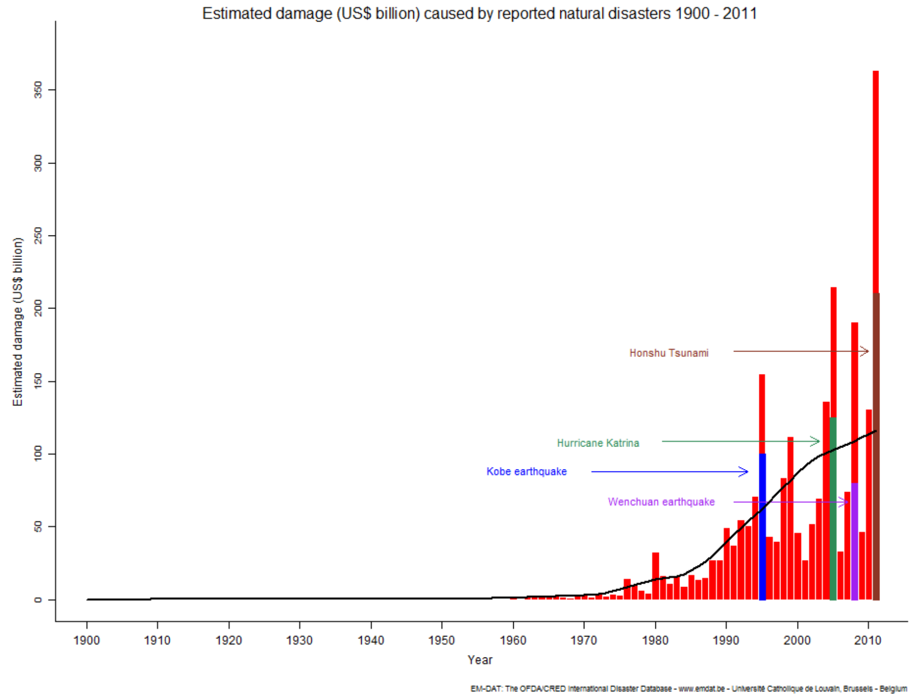


Figure 5: Estimated damage cost by natural disasters from Em-DAT (Emergency Events Database, 2014)

Counting the types of disasters by number of reports over the past 100 years highlights that hydrological disasters such as floods, are also a prominent issue. Data from national Geophysical Data Centers reports that the top three causes of disasters since record keeping began are flood, earthquakes and cyclones (CBCnews, 2010). Earthquakes have also been responsible for triggering other natural disasters, such as avalanches (e.g., Peru, 1970), and tsnuamis (e.g., Indian Ocean, 2004).

This thesis focuses on disasters that are based on hydrological and climatological causes and uses datasets that are drawn specifically from major storms and storm-related floods.

2.2.4 Emergency alert guidelines

Whilst it is clear that natural disasters vary in their impact in both damage costs and frequency, what prompts emergency services to raise the alert level is different than what would be considered disastrous by people. For a person who is victim in a serious situation, it is disastrous (Postle, 1980). But for emergency services an event is disastrous when it affects a significantly large number of people. Therefore, even though the terms hazard, emergency and disaster all describe negative consequences of a situation and calls for attention, the criteria that escalates a hazard or emergency to a disaster differs in each disaster situation.

Emergency services around the world each have their own set of criteria that allow them to redefine current situations and raise an alert. The Queensland Emergency Alert Operational Manual (Emergency Management, 2003) presents clear guidelines on this topic. The Queensland Emergency Alert Operational Manual suggests six criteria to consider when an emergency alert is issued:

- Certainty: whether the impact will be within 12 hours and what factors can increase or decrease the threat
- Severity: how bad the effect will be? Will it be loss of life or significant damage to infrastructure and environment
- Timeframe: is the warning going to be effective before the disaster hits?
- Frequency: is this event going to occur too often and therefore make this alert ineffective in the future?
- Similarity: does this alert overlap any other existing warning?
- Action: does the community needs to act based on the alert?

In addition, the Queensland Department of Community Safety also outlines which situation is likely to need more attention (Table 1).

Definitely	Probably	Possibly
Severe bushfire	Chemical, biological, radioactive threats	Localised very severe hail up to 4 cm in diameter
Imminent storm surge	Imminent severe cyclone of	Localised severe

and 0.5 metre high tide	Cat 3 and higher	thunderstorm with destructive winds and / or intense rainfall
Hazardous material release	Localised severe hail of 4 cm diameter	
Tsunami of more than 1 metre height	Major flood	

Table 1: When to raise an alert (Emergency Management, 2003)

The point is, these criteria are related to how badly people or infrastructure are affected (Coombs, 2011). A severe storm in the middle of desert will not raise the necessity for an alert, while a storm of much lesser strength in a highly populated area will. Thus, even if the magnitude of a disaster can be measured by scientific sensors (e.g. seismic sensor for earthquake), the severity of a disaster is often determined based on how many lives were lost (Smith, 2013), and how much of the damage that was inflicted directly affected people. Therefore finding how people have been affected may provide emergency services with more actionable information. This thesis looks at how to find out **information from people** in order to help the people in the affected areas.

2.2.5 Role of emergency services

As mentioned in the previous section, it is the emergency services who classifies if a situation is considered a hazard or disaster. This section introduces what is an Emergency Service and what is their job scope in order to understand their roles and responsibilities in disaster and why actionable information is important to them.

According to Haddow et al. (2010) emergency services are organisations whose main job is to deal with risk and risk avoidance. This means their role is not just limited to assessing a situation, but to be involved in every phase of a disaster. Although emergency services are most visible immediately after a disaster, as they are on the ground to conduct and coordinate relief efforts, their involvement goes far beyond the moments of disaster and post-disaster (Phillips, Neal, & Webb, 2011; Reynolds, et al., 2002). Emergency services organisations are also involved in disaster management planning and response, as well as in educating communities to help them become more resilient. The role of emergency services organisations can be better understood through the discussion of the disaster management cycle in the following section.

2.2.6 Disaster management cycle

As emergency service organisations aim to reduce or avoid damage and loss from natural disasters (or hazards) they need to ensure rapid actions are taken when there is a hazard or disaster. In order to do so, there needs to have an ongoing process of activities (e.g. educating communities about disaster) that goes on throughout the year. Therefore, even though this thesis focuses on the response phase of disaster management, understanding the various phases of a disaster is useful to understand the overall role of emergency services. To do so, this thesis draws on disaster management cycles and disaster life cycles, as they illustrate on going activities taken by emergency service organisations.

As most countries have disaster management organisations, many versions of this cycle have been developed to categorise the disaster management activities. Some cycles describe four phases (Mitigation, Preparedness, Response and Recovery), while others suggest up to seven phases that include education and prevention (Kramer, 2009). A National Governors Association (from U.S.A) report in 1979 as cited in Phillips et al. (2011) established the four phases (Mitigation, Preparedness, Response and Recovery) as the main group within the cycle, and has been adopted by most emergency service organisations around the world. Although different countries use different names of the phases (Phillips, et al., 2011) such as Australia's Prepare, Respond, Recover, Prevent; and New Zealand's Four R: Readiness, Response, Recovery and Reduction, these management cycles generally share the same features and activities. The following section describes the four phases (Mitigation, Preparedness, Response and Recovery) and their needs.

Figure 6: Four phases of disaster cycle introduced by National Governors Association in 1979

Mitigation The idea of mitigation is to eliminate or decrease any possibility of a disaster happening. This generally includes consistent effort by emergency services, as well as other organisations (mostly government bodies), to disallow activities that can increase a hazard and become a disaster. For example, a national earthquake hazard reduction program by the USA federal government conducts basic and applied research in seismology and infrastructure engineering, provides requirements for land use planning, creates list of materials use based on location, and supports the global Seismographic network to pinpoint earthquakes in real time (Haddow, et al., 2010). Countries around the world have similar programs for managing floods and tsunamis by building dams and walls, which are aimed at preventing disasters as much as possible.

This phase happens before a disaster and is often introduced again after an area has recovered from the disaster. The key contributing factors for this phase are education and communication, which can range from educating people about where to build their house, to making them aware about climate change and the risk they may face. The mitigation phase also usually involves authorities such as local councils or other governing bodies, as many of the mitigation tasks involve policy and legislation activities. Understandably this phase is a long term continuous activity that goes on hand in hand with nation building and development.

Preparedness Preparedness consists of activities that prepare a community on how to respond when disaster strikes (Altay & Green III, 2006). Preparedness is often considered as the building block of emergency management because in the case of mitigation failure, this phase prepares people to face the disaster. While mitigation works at a much larger scale such as policy making, preparedness prepares people in specifically how to face the disaster, by creating evacuation planning or training ordinary people to be volunteers during a disaster period.

Like mitigation this phase also happens before a disaster. Typical activities in the preparedness phase involve recruitment and training. While recruitment could be for emergency services or for volunteer groups, training can involve concerned citizens as well. Constructing emergency operation centres and shelters also falls under this area, although it can overlap with the mitigation phase.

A significant part of preparedness training involves training on the emergency operation plan, which usually consists of several parts. The first is the base plan that contains the details of the plans needed during emergency situation. The second is an operational plan that describes what type of help the emergency services can provide. The third plan, the hazard plan, goes further in creating situational awareness and detailing an action plan.

Response The response phase is the actions taken after a disaster to save lives as well as to prevent further damage of environment and property. This phase deals with providing emergency assistance for people in need. The first step usually is to activate the emergency operation plan, which consists of activities such as the mobilising of personnel and relief. The relief works involve providing basic human needs such as food, water, shelter and medical assistance (Todd & Todd, 2011). The second is the activation of emergency operation centre and the opening of shelters and other preparations for provision for mass care (Simpson & Hancock, 2009). This is followed by search and rescue, infrastructure protection, recovery of lifeline services (Si, Wang, Hu, & Zhou, 2011), fatalities management and other emergency rescue and medical care (Noreña, Yamín, Akhavan-Tabatabaei, & Ospina, 2011).

This phase happens during and immediately after a disaster and the duration of this phase can vary based on the type of disaster that occurred. For rapid disasters such as earthquake it can last for few weeks to few months. For prolonged disasters such as flood or drought, this phase can last months to even years.

The biggest challenge at response phase is the rapid and effective mobilisation of personnel, leadership, resources and information according to the Department of Community Safety, Queensland Government (2011). This view has been echoed by other researchers (e.g., Todd & Todd, 2011; Zhou, Huang, & Zhang, 2011), who have emphasised the importance of rapid action, clear awareness of responsibilities, logistic application and the collection of relevant information. The DCS, (2011) argues that the faster and more effectively that disaster responders can respond the more they can reduce community harm.

This view of the need to respond as quickly as possible to save lives is not always agreed upon. Telford, Cosgrave, and Houghton (2006) argue that, contrary to this belief, disaster affected people are often not that helpless and the first step of life saving actions are often handled by people locally. In addition, these local people may also be assisted by people from nearby areas. The role of the state remains important, however it have been argued the significance of emergency services in the immediate aftermath of a disaster has been overstated (Lorch, 2005). The help of the emergency services and the state authorities is necessary when the local community's capacity to cope is exceeded (McConnan, 1998).

In the Tsunami Evaluation Commission (TEC) report, Telford (2006) instead suggested that, information immediately after disaster is the most valuable resource. This is because access to high quality information allows both emergency services and local responders to provide a better emergency response and to plan recovery. An inability to gather accurate, or at least actionable information, creates other problems too. According to Goyet and Morinière (2006), a lack of information creates ignorance among emergency services and can mislead both international donation organisations as well as community. Furthermore poor information flow with emergency services is one of the biggest sources of dissatisfaction, anger and frustration among affected people (Harrald, 2006). For this reason Telford et al. (2006) argues that it is valuable for emergency services to compile and analyse information from various sources to gain accurate information regarding the situation.

The importance of using multiple information sources was echoed in the 2006 Indian Ocean Tsuanmi Evaluation report by Goyet and Morinière (2006). According to Goyet and Morinière (2006) the initial assessment of the tsunami was done significantly based on media reports. Although there were pre-assessments done by various other agencies, it was often not sufficient. Furthermore, while in more industrialised countries there are emergency services, in developing nations immediate disaster responders are often locals in that area (Telford, et al., 2006), who often don't have access to such emergency services report. In addition, disaster responders in developing nations may not have access to channels (e.g. mass media, emergency call service) to voice out their needs as well.

As it can be seen, in a disaster situation having actionable information is an extremely critical component of disaster response. In the past, with the extreme amount of chaos that a natural disaster can create, it was often very difficult to find accurate actionable information. Fortunately with technological changes are increasing avenues for locals to express their needs, and these can be extremely useful for gathering information.

Recovery Even though this phase of the disaster life cycle happens after a disaster, it can start very quickly as it addresses recovery, rehabilitation and reconstruction (Todd & Todd, 2011). Most of the actions taken post disaster are targeted towards re-establishing the normal activities of the society as early as possible (Queensland Government, 2012b).

The initial activities at the recovery phase usually involve clearing up the damage or the debris (Fetter & Rakes, 2012), as well as burial of human and animal remains. This is then followed by longer term recovery activities such as rebuilding key infrastructure such as roads, bridges, hospitals, schools. Financial assistance to the general public, as well as local governments, are commonly provided at this phase to bring the lifeline services back. This recovery period often not only covers basic needs, but also addresses the mental health of the people affected.

Restarting the cycle At the end of the cycle, mitigation starts. And this new phase disaster management draws on what they have learnt from having gone through the above cycle, and may include improving physical infrastructure and community resilience. Improving the performance of emergency services using the information gathered through various sources, including social media, is crucial. The importance of this type of information is addressed in the discussion of the "Post Hyogo Framework" in the following section.

2.2.7 Hyogo Framework for Action

Although this thesis is focused on identifying relevant information from social media, any discussion about natural disaster and emergency response is incomplete without the mention of the Hyogo Framework. The Hyogo Framework for Action (ISDR, 2005) is a framework adopted by 168 countries around the world to build more disaster resilient nations and communities (Hall, 2007). The framework was developed in Hyogo province of Japan where approximately 6434 people lost their lives and more than $100 billion worth of property was damaged due to Kobe earthquake in 1995. The post-earthquake assessment prompted the Japanese emergency services to propose this framework at the World Conference on Disaster Reduction in 2005. The aim of the framework was to assist countries to reduce vulnerabilities and the risk of hazards, in recognition that risk reduction efforts need to be systematically integrated. The initial timeframe for implementation was from 2005 to 2015

The framework (Figure 7) identified five main gaps and challenges that needs to be addressed. They are:

(a) Governance: Ensure that disaster risk reduction (DRR) is a national and a local priority with a strong institutional basis for implementation

(b) Risk identification, assessment, monitoring and early warning;

(c) Knowledge management and education: Use knowledge, innovation and education to build a culture of safety and resilience at all levels

(d) Reducing underlying risk factors;

(e) Preparedness for effective response and recovery: Strengthen disaster preparedness for effective response at all levels (ISDR, 2005, p. 14)

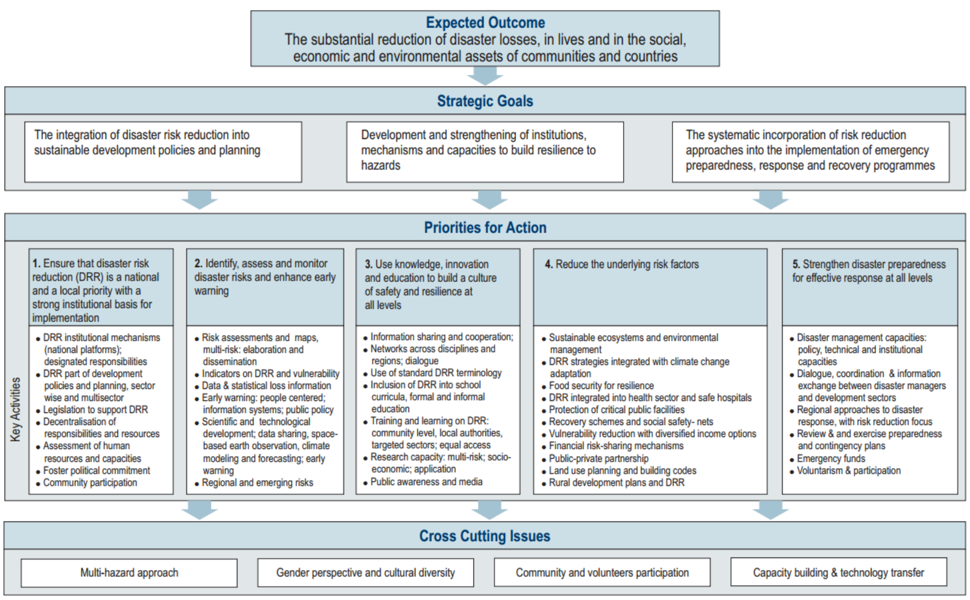


Figure 7: Hyogo Framework for Action (ISDR, 2005)

One common criticism of Hyogo Framework is that it is extremely generic and does not provide specific guidelines for action (Hannigan, 2013; Rasid & Paul, 2013). However, such umbrella guidelines can be more useful than specific guidelines because they can allow for yet unrealised technological changes or system improvements. For example, in this framework, importance of information has been mentioned in two of the five sections, Risk identification, assessment, monitoring and early warning and Knowledge management and education, without providing specific guidelines on how tasks should be accomplished (ISDR, 2005). Considering that the guidelines were proposed in 2005, and therefore are likely to have been written in 2004-2005, it is unsurprising that harnessing information from digital sources such as blogs, which were utilised in 2005 (Hurricane Katrina) (Macias, Hilyard, & Freimuth, 2009), or social media (seen in recent disasters).

The framework highlights that reliable information is valuable to emergency responders. This research looks at how to identify such information from social media, because, as the next section explains, social media contains a lot of information after a natural disaster.

2.2.8 Emerging from disaster management literature

As the literature above demonstrates responding to a natural disaster is a complex affair that involves long term activities as well as rapid actions. Depending on the phase and type of disaster, the need and pace of activity varies drastically. Although different phases of disaster have different needs, the most important phase – the response phase – has a few critical success factors identified by various literatures and the Hyogo framework. They are:

A) Accurate assessment and awareness of the situation

B) Mobilising resources based on an accurate estimation of need

C) An appropriate leadership and structure

A common component among these factors is accurate and usable information. Bodenhamer, (2011) identifies the role of quality information gathering as a critical success factor for making decisions on all levels. Both disaster organisations and the general public can benefit from usable information at times of disaster. The TEC report (2006) has further pointed out the need for information to identify who to involve from the community in relief operations. Various other government articles such as Queensland Reconstruction (Queensland Government, 2012) emphasises involving people on the ground for both information dissemination and information gathering, in order to find useful and reliable information during times of disaster.

In Chapter One it was mentioned that finding actionable information immediately after disaster could reduce community harm. As emergency services emphasise that disaster impacts are measured based on their level of community harm, if information about the disaster can be gathered from the community who are affected by the disaster, it may help to address the information gap. However, finding such information after a natural disaster is challenging (UNISDR, 2013) and in. Therefore it comes as no surprise then that governments around the world have started to consider the use of social media during disasters to gain critical intelligence on emergencies and natural disasters (Rothery, 2012), as the use of social media has increased globally. Based on a synthesis of the literature, information that can be drawn from social media and is needed by emergency services can be grouped into following categories.

Need estimation and resource mobilization The first category of information needed after any disaster is in relation to basic human needs, which includes food and water. Such information can be found in social media as people often go to social media to report about need of basic necessities followed by requests for shelter and medical assistance, as well as reports of public and private property damage (Palen, Starbird, Vieweg, & Hughes, 2010). By analysing the areas in which are communicating about missing persons in their social media feed, emergency services can estimate which specific areas might have been the most affected (Imran, Elbassuoni, Castillo, Diaz, & Meier, 2013). Information about animals can also be useful as some people would not want to leave their pets behind, which means emergency services need to bring the animals along with the people they are rescuing.

Updated information The second group of information is in identifying up to date details regarding a disaster area. It is often difficult to get the entire picture immediately after a disaster. As new and up to date information often appears in social media after disaster, it can be used to update existing information and current estimates of damage and loss of lives.

Challenges There are however several key challenges in gathering intelligence from social media and incorporating that information for critical decision making. Two of the most notable challenges are identification (Platt, Hood, & Citrin, 2011; Seo, Mohapatra, & Abdelzaher, 2012) and verification (Mendoza, Poblete, & Castillo, 2010). As of now there are no clear guidelines that identify what type of information is considered relevant for emergency services and what should be excluded. Therefore, even though identifying relevant information from social media has been highlighted repeatedly in disaster management literature, in practice it is still uncommon to fully integrate social media in emergency response efforts (Pipek, Liu, & Kerne, 2014).

Therefore this thesis focuses on one component, identifying relevant information from social media after a natural disaster. Although verification is another key research area in intelligence gathering, in order to limit the research to a manageable scope this thesis focuses only on identification. The next section describes, synthesises, and evaluates existing social media research to determine what is known about how to identify information from social media that is relevant for emergency services to use for disaster response.

2.3 Twitter in Everyday Life and Crisis Events

Previous sections of this literature review discussed the needs of emergency services that can potentially be drawn from social media. This section introduces the literature from the second discipline of crisis informatics – media and communication – focusing on social media studies in crisis communication. After introducing currently popular social media sites, it will present the rationale for the focus of this research on Twitter. The review will then explore the opportunities and challenges for emergency services to use Twitter to gather information.

The reason for the growing interest in social media to find disaster relevant information is, in recent years social media websites (social networking sites) have heavily influenced the way people communicate socially or interpersonally (Baym, Zhang, & Lin, 2004). People have become more prone to discussing their life events publicly (Stutzman, Boyd, Marwick, Lampe, & Ellison, 2008). With short messages or status updates, they do not need to invest too much time to engage in discussion and debates that matters to them (Stephens & Malone, 2009). This has made sharing information, reporting about surroundings or just engaging in daily chatter over social networks an easy task (Java, Song, Finin, & Tseng, 2007). Although for each individual it is their own voice, the aggregation from millions of people have made these social networking sites a source of information for news and an avenue for research (Bruns & Burgess, 2011a; Jordaan, 2013; Kwak, Lee, Park, & Moon, 2010). In addition, as increasingly more people join and share information and day to day life happenings in social media, it is increasingly becoming a valuable tool for gaining insights about human behaviour.

While the underlying functionality of social media sites are similar, the way the sites function and the type of users they attracts can be drastically different (Lipsman, 2009). Some social networking sites focus on users and their life (Facebook), some focus on the message (Twitter), some focus on collecting and discovering ideas (pinterest), some focus on knowledge creation (Quora), while some other focus on pictures (instagram), or finding jobs (linkedIn). This differentiation in functionality attracts different types of audiences as well as different types of activity, which can range from using the networks for personal reasons (Deller, 2011), or for work related purpose (Ehrlich & Shami, 2010), or to support revolution in order to topple a government (Lotan et al., 2011). Since the activities are often drastically different, different networks presents different opportunities and challenges for research. The next section provides a list of key social networks with brief descriptions of features, functions, demographics and the rationale for selecting one of the social media sites in this research.

2.3.1 Overview of social media sites

As mentioned in the previous section, the reasons people use certain social networks over others depends on a combination of the features, functions, demographics and various other components. It could be because their friends are there (Westlake, 2008), or it helps them to stay in touch with what is going on around them (Zuckerberg et al., 2010), or they have created their own audience (Tufekci, 2008). The bigger the user base a social network has, the higher the chance that people will use it more often as the likely audience is there (Deller, 2011). At present the most popular social network is Facebook, which has 1.28 billion monthly active users (Facebook, 2014). Based on the numbers reported in their website, the second most active users belong to Google+. However, even though Google+ reports they have 540 million users, it does not say if they are solely a Google+ user, or if they are gmail users who also have account in Google+ and log into their integrated account. Similarly, Twitter reports over 288 million monthly active users, even though around 8% of twitter accounts are reported as automated accounts or bots (Zi, Gianvecchio, Haining, & Jajodia, 2012).

One thing can be observed from the numbers of monthly active users – each of the above mentioned social network has a large number of users. Even discarding the total monthly active users as problematic (Wagner, 2015) and looking only at the usage do not help to narrow down the scope of this research. From a usage point, in Twitter, the total number of daily tweets has gone from thousands to half a billion within five years (Twitter Inc, 2015), and the numbers of tweets are increasing daily. Users upload an average of 60 million photos on Instagram daily (Instagram, 2014). More than 890 million people log in to Facebook daily and spend on average 21 minutes performing various activities (Facebook, 2014). Reddit claims to have 202 million active users each month viewing more than 7 billion pages and often conversation happens as readily as other social networks (Reddit, 2015). There are more than a billion monthly active users in YouTube and it is common to find videos from disasters first responders in YouTube (YouTube, 2015). Therefore analysing multiple social networks for crisis communication would require a massive effort, whilst focusing on a single social network makes this research more managabale by focusing on information collation of emergency services from a single social network. The following list therefore provides a brief outline of the best known social network websites, why people use them for, their limitations and how easy it is to discover their contents, along with active monthly users as of early 2015 (Table 2).

Name	Monthly active users*	Common usage and challenges for research	Accessibility, search and discovery
Facebook	1.4 billion	Users share their life events with mostly close groups of friends. Need to be a friend to access contents.	Password protected, search for users, places.
Twitter	288 million	Apart from sharing daily life, users tend to share breaking news impulsively.	Public, can search with hashtag or keywords to find tweets
Sina Weibo	167 million	Limited to Chinese speaking audience and used for sharing both life events and breaking news.	Public, can search for user and their posts
LinkedIn	200 million	For professional networking and finding job opportunities, people only update when they are looking for job.	Semi public. If logged in, able to see more information
Google+	540 million	Most commonly used for sharing with niche Group members. The largest sectors are technical sectors.	Public, posts and community
Quora	11 million	Knowledge creation via personal stories. Still in its early stages of usage and there is no way to verify if the content is authentic.	Semi public. Need to login to read more than one story
Pinterest	40 million	Sharing of creative ideas. The largest share of contents are do-it-yourself items.	Public, discovery through pins and boards
Instagram	300 million	Photo sharing. Often used by celebrities.	Public, can access with hashtag
Reddit	202 million	Stories and discussions around various topics. Highest voted stories appear in the front page. Often controversial	Public, discovery through subreddits.
Youtube	1 billion	Users shares wide range of videos. After disasters it is common to have crisis related videos to appear here.	Public, discovery through search or suggested videos

Table 2: List of notable social networking sites as of early 2015

Based on the Table 2, it can be seen that not all social media sites are useful for this research. For example, Pinterest or Quora are an unlikely source for identifying disaster information quickly because, although they have large numbers of active users, the focus is on quality content creation rather than breaking news about an event. Similarly, although Sina Weibo has been used in disaster situations (Yang, Yu, Liu, & Yang, 2012), due to the language limitation, it is only useful for Chinese emergency services. Google+ may appear to have a large number of active users but they are hardly mentioned in the literatures related to crisis situations mostly because Google does not disclose if these users are Google+ users or they are Gmail users who also have an automatic Google+ profile. Instead, for the purpose of finding disaster information, researchers find Facebook, Twitter (Huang, Chan, & Hyder, 2010) and Instagram (Aulov, Price, Smith, & Halem, 2013) to be the three most relevant social media sites.

However, as a primarily photo sharing platform Instagram is still not as prominent as Twitter and Facebook in crisis informatics literature. By drawing on the concept of ever increasing importance of Twitter and Facebook (Mitchell, Rosenstiel, & Christian, 2012) suggested in the article "What Facebook and Twitter mean for news" that, social media sites in general have now become a pathway to news and are often seen as a place where reporters get ideas for their news rather than the other way round. The difference between Facebook and Twitter is that Facebook's walled garden approach makes it less useful as a breaking news platform (Murthy, 2011; Stassen, 2010). The platform specific limitations are revisited in detail later in this chapter.

In conclusion, the majority of the studies across the crisis communication literature noted in this review have highlighted the critical role of Twitter in breaking news (Bruns & Burgess, 2011; Kwak, Lee, Park, & Moon, 2010). Given the focus of this research on identifying information from disasters that is relevant to emergency services, it is expected that information from Twitter often contains breaking news, making Twitter a highly relevant platform as a news medium. The following section defines Twitter as a medium before addressing its suitability as a news medium in a crisis situation.

2.3.2 Twitter as a medium

Twitter has established itself as a ‘new’ medium (Kwak, et al., 2010) that some researchers argue complements older media (Harrington, Highfield, & Bruns, 2012) and others argue outperforms traditional news agencies (Petrovic et al., 2013). In order to understand the difference in standpoints on Twitter as a medium among media studies researchers, it is first necessary to address what differentiates Twitter from other forms of media.

A key aspect of Twitter is the brevity of the message (Zhao & Rosson, 2009). Compared to any other medium, including other social media sites, a tweet is extremely brief. However, instead of being a hindrance, the limitation of only writing 140 characters have been cited as one of the reason for Twitter’s explosive growth because it allows time starved modern users to express their thoughts and feelings extremely quickly (Java, Song, Finin, & Tseng, 2007). Since composing a tweet generally requires less time and thought investment than writing a blog or a news article, it is no surprise that people often flock to Twitter to share all kinds of opinions and information, ranging from comments about their favourite TV shows, to a plane crash or natural disaster (Farhi, 2009).

This abundance of expression in the form of tweets, along with the flexibility of following another prominent user, topic (with hashtag), or redistributing another user’s tweet to an individual’s own followers with ease (via retweet), has fuelled an explosion of participation from average users in reporting newsworthy events (Gupta et al., 2013; Hermida, Siapera, & Veglis, 2012) – often before they get broadcasted by traditional media. Kwak, et al (2010) stated that their “preliminary results confirms the role of Twitter as a media for breaking news”. This trend can be observed from other notable example such ash live tweets about Osama Bin Laden capture (Hu, Liu, Wei, Wu, Stasko & Ma, 2012), death of singer Whitney Houston (Lau, Collier & Baldwin, 2012), Boston Marathon bombing (Cassa, Chunara, Mandl, & Brownstein, 2013). In addition, Dewan and Kumaraguru (2014) have used Facebook, Google Plus and Twitter to analyse 29 major events and found that Twitter is the fastest among all in breaking news, a view that is supported by other researchers as well (Osborne, Petrovic, McCreadie, Macdonald, & Ounis, 2012; Dewan & Kumaraguru, 2014)

This has resulted in Twitter being used to predict stock market results (Bollen, Mao, & Zeng, 2011), for aggregating consumer opinions about brands (Jansen, Zhang, Sobel, & Chowdury, 2009), predicting election results (Tumasjan, Sprenger, Sandner, & Welpe, 2010) or communicating after a natural disaster (Acar & Muraki, 2011). These are some of the reasons why some researchers argue that Twitter outperforms traditional media in speed of information sharing, since it often contains breaking news (Neuberger, Vom Hofe, & Nuernbergk, 2013).

There are of course other cases where Twitter complements traditional media. Due to its dialogic transmission system, it has been used with popular TV shows to create real time engagement (Doughty, Rowland, & Lawson, 2012). Although in most cases such programs use Twitter as an additional engagement layer, entertainment programs such as "Tweet Love" in Japan has used Twitter to find potential match making couples from audience's tweets (Sakamoto & Nakajima, 2014). And Twitter's ability to complement traditional media is not just limited to entertainment shows. According to Zhao et al. (2011), important world news topics are likely to spread faster through Twitter than other types of news. Twitter's CEO also suggests that Twitter is meant to complement news media and not to replace them (Isaac, 2013).

Taken together, these studies suggest that Twitter is a prominent news medium of modern times. Whether it outperforms or complements traditional media is a debatable topic. What is evident from these studies is that Twitter has enabled people not to rely on specific media institutions to get their news and rather to broadcast their own opinions to their followers. In addition, news outlets are providing more opportunities than ever before for the public to contribute to professionally edited publications through active participations via mediums such Twitter (Hermida, et al., 2012). These opportunities, along with the large volume of messages, has made Twitter a strong medium in its own right. The next section addresses the question of whether Twitter is a relevant news medium for emergency services.

2.3.3 Twitter as news medium

In broad terms, some of the key criteria for a medium to be considered a prominent news medium are the ability to deliver news that is timely, significant, credible, and which occurred nearby (Harcup & O'neill, 2001). News is time sensitive, and with its potential for realtime delivery (Bandari, Asur, & Huberman, 2012) Twitter has emerged as a powerful news source (Sankaranarayanan, Samet, Teitler, Lieberman, & Sperling, 2009). Although information credibility in Twitter remains a concern (Mendoza, et al., 2010), at times Twitter has proven to be able to break news faster than others and has been described as an ambient journalism platform (Burns, 2010; Hermida, 2013).

Nevertheless, it is important to determine what type news usually gets broken on Twitter compared to other traditional news media. Since this dissertation looks into identifying relevant information after a natural disaster, it is important to find out if news stories that would be useful for emergency services can be found in Twitter. Some recent events show that such information can indeed be found in Twitter. For example, when U.S. Airways flight 1549 landed on Hudson River, the news was broken via Twitter by Janis Krum who took a photo and tweeted about it (Lenhart & Fox, 2009).

This trend of live tweeting from location can also be seen after a natural disaster (Reynolds & Seeger, 2012). After the 2011 Japan tsunami, there were about 5,500 tweet per second related to the tsunami - many of those originating from Japan. Similar trends were seen during the Mexico earthquake in 2012 (Crooks, Croitoru, Stefanidis, & Radzikowski, 2013), Queensland flood in 2010-2011 (Bruns, Burgess, Crawford, & Shaw, 2012). Based on the recent events, it can be suggested that, even though twitter only has 140 characters and people may tweet about the events individually without knowing about other tweets, it became news in Twitter because details of what happened were disseminated instantly and were repeated throughout the network.

In view of all that has been mentioned so far, one may argue that Twitter fulfills many of the criteria of news medium: significant information is spread faster than other types of information, nearby events get reported earlier than traditional media and most importantly, information can be found extremely quickly (Machin, 2011). The next section summarises why Twitter was selected for this research on disaster management services' access to critical information.

2.3.4 Twitter in crisis communication

The studies presented so far suggest that Twitter is an excellent venue for disseminating various types of information extremely quickly. Regardless some critics argue that Twitter is only used for a social presence (Dunlap & Lowenthal, 2009) or posting "Fried eggs and beans on toast for breakfast today" (Launer, 2013). However as described earlier, Twitter played a big role in sharing crisis information around the world from Queensland flood (Bruns, et al., 2012), tsunami in Japan (Acar & Muraki, 2011) to hurricane Sandy (Guskin & Hitlin, 2012), and its use in such situations continues to increase (Bruns, 2014).

One can argue that because so many people are sharing information, it may be difficult for emergency services to act on it. However, examples from disaster situations suggests otherwise. For example, after the earthquake in Japan in early 2011, a Japanese Twitter user reached out to the American Ambassador in Japan, John Roos, who was heading the American rescue operations after the earthquake with two following tweets: "Kameda hospital in Chiba needs to transfer 80 patients from Kyoritsu hospital in Iwaki city, just outside of 30km range" "Some of them are seriously ill and they need air transport. If US military can help, pls contact (name withheld) at Kameda" (Harris, 2013). According to USA today, “The ambassador alerted the U.S. Embassy's defense attache, who passed it down through the U.S. military chain of command, says Fuller, Roos' aide. An hour or so later, Fuller says, "we got a note back," saying the patients would be evacuated by Japan's Ground Self-Defense Forces. Two tweets had mobilized troops” (Sternberg, 2011).

Such stories are rather norm instead of exception. Similar situations have been observed during other disaster situations, such as hurricane Irene in the U.S.A. (Abbasi, Kumar, Filho, & Liu, 2012). Government and crisis response organisations have been embracing social media increasingly. This is partly due to the ability to communicate directly to the people in need (McNutt, 2014), and partly due to the increased expectation from people that they will get assistance if they post in social networking sites (American Red Cross, 2011).

This emphasis on social media was especially evident in the Queensland flood (Bruns, et al., 2012), where Queensland Police Service (QPS) rose to prominence on Twitter in just 3 days (Bunce, Partridge, & Davis, 2012; Dufty, 2011). Recognising a new avenue where they could post updates and reach people extremely quickly, QPS media used social networking sites heavily, and these became a major source of information in the times of crisis.

This embrace of social media by authorities had not been limited to natural disaster situations, but also other crisis events such as the Boston Marathon bombing (Cassa, Chunara, Mandl, & Brownstein, 2013). The tweet request from Boston police for the video “Boston Police looking for video of the finish line #tweetfromthebeat via @CherylFiandaca” was retweeted more than 3000 times (Rogers, 2013). Similarly “#WANTED: Updated photo of 19 year-old Dzhokhar Tsarnaev released. Suspect considered armed & dangerous” posted at 11:32 PM - 19 Apr 2013, just 4 days after bombing was retweeted 13,574 times and helped to locate the suspect. The success of using Twitter to catch the suspect within a week was documented in the Huffington Post article, “Boston Police Twitter: How Cop Team Tweets Led City From Terror To Joy” which portrayed how Twitter can be useful for emergency services in a crisis (Bindley, 2013).

Although for the purpose of this thesis the role of Twitter in crisis communication and information diffusion is limited to natural disasters, such examples show that Twitter has been increasingly used by both the general public and emergency services in crisis communication. In addition, in countries where news media is known to be censored, people look to micro blogging platforms for unbiased news. For example, in the Yanjin (China) earthquake in 2006, it was reported that Twitter was the place that broke the news (Qu, Huang, Zhang, & Zhang, 2011). In addition, as people generally trust their friends and families more than authorities, people are more willing to believe crisis related news when it comes from known people (even in the form of retweet), than the media or government (Qu et al., 2011).

2.3.5 Selecting Twitter for this research

Earlier sections have provided an overview of prominent social media networks, including Facebook and Twitter, which have both become a 'go to place' for news reporters. However, as this section shows, Twitter is a more prominent contemporary news medium among social networks and it is most suitable for breaking news. It is therefore the platform that is most likely to contain relevant information even though Facebook may contain similar information as well. This section presents a rationale for the selection of Twitter as the platform for this research.

The first issue emergency services face with regard to Facebook is the restricted membership and access to information based on having to be added to a network as a 'friend' (Dabner, 2012). Although most Facebook pages are publicly available (Dabner, 2012) and often host useful and relevant information after a disaster (Bird, Ling, & Haynes, 2012), to post a message in the Facebook page the user has to navigate to the page and post in that page. At present a Facebook user is unable to post freely to another user's or groups' Facebook page from his or her own status update. Therefore to seek for help from emergency services, the user has to go to the emergency services page and post there.

Such limitations on posting messages during a disaster are problematic for emergency services for a number of reasons. First, unless the page is already well established and publicised, the user may not know where to get help. Since popularity in social networks can change quickly, and authoritative pages may not always be popular. From an intelligence gathering perspective it is even more troublesome since emergency services are unable to automatically extract disaster relevant information from a user's personal status unless the user is a friend of the emergency services account. Although emergency services can look for other pages related to an event, it would be difficult for emergency services to monitor all the pages in the Facebook network.

An alternative, and arguably better approach would be to search through Twitter status via API since in Twitter such messages can be extracted from an user's own status. A tweet is openly available and accessible without having to 'follow' a person or a public page (unless it is protected, which would go beyond the scope of this thesis). It is also possible for emergency services to find important information through the use of the 'hashtag' (DeMers, 2013) or keywords without the user having to contact them directly.

Furthermore, despite having a smaller number of users, Twitter users serve as multipliers for spreading information (Neuberger, Vom Hofe, & Nuernbergk, 2013). The ability to spread information so rapidly is one of the reasons why the research to date on social media and natural disasters has tended to focus on Twitter, despite that Facebook has more active users, and both social media types have impacted disaster responses. As this thesis focuses on gathering information in a crisis situation, and Twitter users have been shown to provide crisis related information without restricting their updates behind a walled garden, Twitter is the social network of choice for this thesis.

Before going further it needs to be mentioned that, it is necessary to keep in mind that density of Twitter user is an important factor in gathering social media information from Twitter. It is not uncommon to have a small scale crisis situation appear huge in social media if that crisis affects a location with large number of social media users compared to a location that does not have ample social media users. Therefore the question of representativeness of data needs to be taken into consideration in any Twitter research.

2.3.6 How Twitter is used in a crisis situation

In order to discuss the activity patterns in Twitter in crisis situation, it is useful to understand how users communicate in Twitter. This is relevant because a well defined communication pattern in other media or platforms, may not apply in Twitter. For example, in Atkinson and Wald (2007) conducted a mass survey on earthquake and collected 750,000 responses to suggest that “did you feel it” is a surprisingly good measure of ground movement. This finding prompted other researchers to use this as an indicator of earthquake, and suggested that it would be a useful measurement tool to identify if an earthquake had occurred from Twitter. However, Earle, Bowden and Guy (2012) found during a five month experiment, that there were no mentions of “did you feel it” in Twitter during an earthquake. Rather, there were mentions of earthquake, shake and other words that were synonymous to earthquake and by tracking those words instead of the whole sentence, Burks, Miller and Zadeh (2014) identified the trajectory of 2011 Tohoku earthquake. This section discusses some of the known communication patterns and the evolution of communication patterns over the years.

Requesting information One of the first things people do after a natural disaster is to look for their family members and friends via calling, texting or any other means possible (Ling et al., 2014). This behaviour is commonly seen in Twitter as well, where people who have friends and family tend to seek information from Twitter (Shklovski, Palen, & Sutton, 2008). The reason people tend to ask for such information from Twitter is, for a specific location to be newsworthy, it either needs to be in an area of importance or an area that is badly damaged. If it is not, it is difficult to find information for that area in the news, especially in the early hours of a disaster (Gupta, Joshi, & Kumaraguru, 2012). Thus in the midst of uncertainty when the total picture of the disaster area is not known, people who's friends and families live in that area may go to Twitter for information about these places from people living in that area who may inform that they are safe or that a certain area is affected.

However, in recent years there has been an increased expectation from users that the authorities are following tweets even though users may not be sure how the authorities might know about the tweet (Stephens & Malone, 2009). In a 2010 survey the American Red Cross found that among the 1048 respondents, 75% wanted or expected to received assistance after they posted a message in social media. This adds additional pressure for emergency services, who now not only are expected to know information from the ground, but also from online (Crowe, 2012).

Updating about surroundings In the previous section the benefit of getting real time information from Twitter that is extremely difficult to get from the other media was discussed (Kavanaugh, et al., 2012; Stieglitz & Dang-Xuan). One area in which this works very well in a crisis situation is updating of temporal information. In the early hours of a disaster location specific information changes frequently (Dodds, Harris, Kloumann, Bliss, & Danforth, 2011). A road might be flooded in the first hour but the water may go down in the second hour or vice versa. It is not possible for media to broadcast such specific information based on locale. In these situations getting updates from people about their area can provide emergency services with helpful and up to date information.

Voluntweeting Another Twitter centric activity is known as 'voluntweeting'. Starbird and Palen (2011) found that after natural disaster a group of people tend to self mobilise into a group of voluntweeters who come forward to assist in relief efforts. In addition to actively tweeting about the situation, users who are present locally also tend to assist physically and those who are not near assist through online channels. This behaviour is similar to how people act after natural disasters; as mentioned by Telford et al. (2006) it is the local residents who are likely to be the first responders instead of emergency services.

With Twitter it goes beyond the geographical boundaries. Even if people are not near the affected area, they can still help emergency services by filtering information that is relevant for them. One of primary example of this was seen during 2010 Haiti earthquake, when many people from various parts of the world used social media, text messages and Ushahidi maps to assist in relief efforts as well as guiding emergency services to find people under the rubble (Muralidharan, Rasmussen, Patterson, & Shin, 2011; Norheim-Hagtun & Meier, 2010).

In addition to gathering information and channeling them to emergency services, these self deployed volunteers also tend to assist in re-broadcasting information that they think are accurate, verify wrong information as well as offer various other kinds of help (Oh, Kwon, & Rao, 2010). Such activities often continue even after the disaster. For example, in the 2011 Queensland flood, the 'Baked Relief' campaign was organised by volunteers through Twitter (and Facebook) to cook and deliver home cooked meals to the volunteers who were cleaning up flood affected areas (Bruns, et al., 2012).

Identifying these self organised volunteers after a disasters can be extremely beneficial for emergency services as they can utilise these additional supports to filter actionable information to help disaster affected people.

Overall, these studies highlight that it is common for people to both update about their surroundings after a natural disaster and use Twitter to look for information about their friends and families. And while doing so, they may use keywords, a full sentence or use Twitter specific ways (e.g. hashtag with keyword) to express their situation. Understanding how Twitter users communicate is useful for information gathering since understanding of the communication pattern can assist emergency services to target other components of a tweet rather than relying on keywords alone.

Automated tools So far this chapter has focused on people's tweeting behaviour. In recent years there has been an increasing number of automated tools, often known as ‘bots’ that tweet during natural disasters (Chu, Gianvecchio, Wang, & Jajodia, 2010), and that can assist emergency services.

Although bots are often perceived negatively due to their usage for spam posts (Lee, Eoff, & Caverlee, 2011), tweetbots linked to sensors from earthquake centres, flood centres, and various other monitoring organisations, can provide relevant information for emergency services. In recent years such sensor bots have been gaining in popularity (Messias, Schmidt, Oliveira, & Benevenuto, 2013), due to their automated updates providing followers with up to date information about a situation.

In conclusion, this section suggests that even though various types of information gets spread in Twitter and some of communicative activities are specific to the medium, a large percentage of the communication pattern is related to the behaviour of the users. Understanding Twitter users through the lens of crowd behaviour theories therefore can provide a useful angle for emergency services.

2.3.7 Twitter uses and collective behaviour theories

This discussion about Twitter users and theories of collective behaviour aims to serve two purposes. The first is to gain deeper understanding about tweeting in a crisis through the lens of collective behaviour theories. The second is to introduce the challenges that are likely to occur in using information from Twitter due to the speed of information spread in Twitter before delving deeper in these challenges in the next section.

In their seminal paper on detecting earthquakes in real time via Twitter, Sakaki, Okazaki, and Matsuo (2010) demonstrated how people act as a “social sensor” during an earthquake. By monitoring tweets they could detect earthquake situations with 96% accuracy and were faster than the Japan Meteorological Agency. Liu (2010) argues that this happens because when a natural disaster occurs, people are likely to retweet or compose an original tweet based on the information that is gathered through the collection of tweets they are exposed to, even if they are not at the scene.

From that aspect, collective behaviour phenomena (Ishii, Koguchi, & Uchiyama, 2013; Lehmann, Gonçalves, Ramasco, & Cattuto, 2012; Liu, Liu, & Li, 2012) is commonly seen in Twitter (Reips & Garaizar, 2011). From various crowd theories, this section analyses three different crowd theories that are related to this study. Having discussed Twitter centric activity in a crisis situation, this section discusses why users perform the activities addressed in previous section. In order to gain a deeper understanding, these activities are discussed through the lens of collective behaviour theories since the behaviour of users in social media can be influenced by who they follow (Romero, Meeder, & Kleinberg, 2011).

Contagion theory To explain contagion theory, the example of a standing ovation in a concert is often used (Miller & Page, 2004). The example illustrates that concert goers are likely to participate in standing ovation even if they don't intend to, if people around them are standing up. Romero et al. (2011) found that such behaviour can be seen in Twitter as well. In many situations, if a user is exposed to hashtags related to same event from multiple users, there is a high possibility that the user will retweet some of the tweets or compose a new tweet that relates to the same event (Romero, et al., 2011). And if the event happens to be a crisis event, the chance of participation is even higher (Glasgow & Fink, 2013).

The findings related to the contagion in Twitter, and the theory itself, are useful to understand one of the most prominent components of Twitter - retweets. In general retweets provide an endorsement of the tweet, often indicating support or agreement to the cause. In terms of a crisis situation, Starbird and Palen (2010) suggested that focusing on retweets is a useful way to collect information because people in the disaster affected area are likely to use the retweet function to pass on information.

However, other researchers have suggested that retweets are one of the main noise (unimportant tweets) generators in Twitter, and in disaster context do not provide any value for intelligence gathering (Macskassy & Michelson, 2011; Sikdar, Kang, O'Donovan, Hollerer, & Adal, 2013). As described earlier, studies on contagion theory and Twitter suggests that people are likely to retweet because they are exposed to disaster news, rather than because they are in the disaster area, thus making retweets irrelevant for emergency services.

To make the matter worse (or noisier), in many cases people retweet during a disaster with the hope that the information will be useful, without knowing if it really is (Harrigan, Achananuparp, & Lim, 2012). In some instances people retweet just because the tweet asks to be retweeted (Malhotra, Kubowicz, & See, 2012). Combining this with contagion theory it can be suggested that contrary to some of the research, retweets are more likely to contain information that is not useful for emergency services. Thus in this research, retweets will be considered the first content to be filtered from Twitter in order to find disaster relevant information.

Convergence theory By definition convergence theory suggests that people form groups with like-minded people, and as a group can intensify a situation by gathering a critical mass (Smelser, 2011). Therefore convergence theory has been used to explain people's behaviour, especially negative behaviour that can occur after a natural disaster (Fritz & Mathewson, 1957).

Convergence theory has also been used to explain online behaviour such as hashtag adoption in Twitter after a natural disaster (Potts, Seitzinger, Jones, & Harrison, 2011). After a disaster Twitter users quickly create many hashtags related to the disaster in question. This can include multi-word hashtags that combines a location with the disaster (Efron, 2010; Tsur & Rappoport, 2012). For example, #QLDfloods for the Queensland flood and #yolandaPH for typhoon Yolanda (or Haiyan) in the Philippines. However Twitter users often settle on a single hashtag (e.g., #eqnz), dropping other alternatives (e.g., #nzeq, #chch, etc.) to form a single channel of information very quickly. However they may also diverge from this again for more specific side conversations (e.g., #bakedrelief), so that these do not clog up the main hashtag.

Understanding such forms of convergence through hashtags is an important part of identifying relevant information for emergency services. This is because if the hashtag does not collect large number of tweets, it is possible that it has been replaced by another more dominant hashtag.

Complex adaptive systems theory Traces of complex adaptive systems can be found in many aspects of Twitter. However before discussing its Twitter manifestations, it is necessary to explain the fundamentals of the theory itself. The central idea of a complex adaptive system is that many small structures (systems or agents) iterate and interact in small groups to adapt to a dynamic and changing environment, and as a by product of this, form a pattern that they may not have intended (Van Ginneken, 2003). Here complexity refers to the dynamic nature and networks of that interaction and adaptive refers to self organisation and mutation. For example, in a weather system each water and air molecule interact and connect with each other in ways that are not pre planned. However at the end of this interaction, a resultant pattern, a cloud, is formed.

This tendency also emerges in Twitter. After a natural disaster people often self-organise themselves and act in their small groups to become the first responders (Vieweg, Palen, Liu, Hughes, & Sutton, 2008). This group of voluntweeters display the core components of complex systems: unplanned emergence, simple rules, self organising and often random.

However, with regards to Twitter usage after a natural disaster, the most relevant component of the complex adaptive system is the co-evolution. The central idea is, anything that is in the system adapts to the changes in the environment the system is in. The similarity between Twitter and the concept of co-evolution can be linked to the frequent changes in the way Twitter works. This can be understood by looking at introduction of features in Twitter both from top down Twitter driven, and bottom up user driven approaches.

Twitter provided communicative features It is very common for a social network, not just Twitter, to change the way it works; adapting the design, interaction mechanisms, or the algorithm, to keep them trendy. For example, as image sharing social networks such as Instagram became widely popular, Twitter started to embed images in the tweet instead of linking to them from other third party sources. Similarly, as autosuggestions became common in other computing environments such as search engines, Twitter introduced this functionality. The reasons such evolution based changes are important for natural disaster situations is that any algorithm that relies on specific features needs to be able to adapt, because what is important today to identify disaster relevant information may not remain important in the next version or API update.

Furthermore, the introduction of new features may change behaviour altogether. For example, as Twitter introduced autosuggestion of hashtags, it is possible that when a natural disaster strikes, people use a hashtag that has been suggested by Twitter itself. Therefore, identifying new features are necessary to find what is important in the Twitter stream.

User generated communicative features One of the most significant user driven adaptations in Twitter was the hashtag. Chris Messina, who originated the idea of the hashtag in Twitter, wanted to create a group management system by using a single word that is already part of the tweet (Figure 8). Thus Messina borrowed the grouping convention used in IRC channels to help users create and discover new groups of conversation on the go (Messina, 2011).

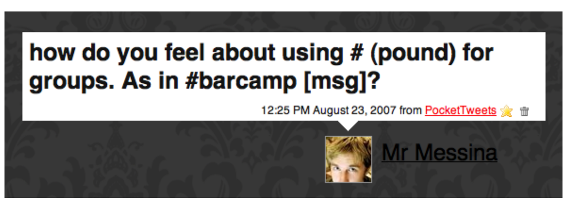


Figure 8: Chris Messina outlines a proposal for Twitter Tag Channels

Initially Twitter was reluctant to use hashtag as it was too nerdy and preferred to use machine learning to group tweets (Messina, 2011), but once twitter embraced the hashtag to group the tweets, it had been used tremendously.

However, reliance on hashtag alone to identify disaster relevant information is risky because there is no guarantee that a dominant and well established hashtag will persist over time, even for a similar event (Lin, Margolin, Keegan, Baronchelli, & Lazer, 2013). Therefore, if disaster responders follow only well established hashtags, they may get limited information. Therefore having a static pre defined hashtag may or may not work at the times of crisis because the usage pattern is likely to evolve, and if the process does not cater to that, the tracking system is unlikely to find important information.

In conclusion, understanding Twitter through the lens of collective behaviour theories starts to highlight potential problems emergency managers are likely to face when gathering intelligence from Twitter. Due to the dynamic nature of the social media and user behaviours the opportunities are often mixed with challenges. Next section addresses some of the challenges faced when collecting data from Twitter.

2.3.8 Challenges with Twitter data

Having discussed the advantages and benefits of using Twitter in crisis communication, this section addresses some of the challenges of identifying relevant information for emergency services from Twitter during a natural disaster. In the previous sections, it has been mentioned that people flock to social media during a disaster to find or to share information. However, during the early stages of a disaster, both locals and people outside the affected area are likely to tweet about the disaster (Bruns & Burgess, 2012). This can make it a difficult task to identify which tweets are likely to be relevant for emergency services.

An example of how the tweeting of locals and onlookers at the same time can be a problem was seen from the tweet counts after the 2012 hurricane Sandy in the U.S.A. In the first five days after the hurricane, there were more than 20 million tweets related to the hurricane (Guskin & Hitlin, 2012). Such large volumes make it humanly impossible to read the tweets to identify which of these are relevant for emergency services. In addition, during the course of disaster situations change quickly, making tweets with updated information more useful than older tweets. Furthermore, natural disasters related tweets not only appear in volume, but also with extreme speed. After the tsunami in Japan in 2011, on average 5,500 tweets were recorded every second (Reynolds & Seeger, 2012). Unless an emergency team has a really large team searching through the dataset, it is extremely difficult to find information that is relevant. And volume and velocity are only two of the challenges; others include identifying the context as well as the veracity and temporality of information (Burgess & Bruns, 2012; Mendoza, et al., 2010; Platt, et al., 2011; Thomson, et al., 2012). The following sections discuss the challenges of identifying disaster relevant information from Twitter in detail.

Volume and velocity Whilst the volume and velocity of disaster related tweets can be extreme, this high usage does not remain constant over a long period of time. During such unexpected events there is generally a large amount of information shared in the immediate aftermath of the incident but the rate drops exponentially afterwards. This is because as time passes, the intensity drops exponentially as the novelty of the information reduces (Hendrickson, 2012), (Figure 9). In Figure 9 the blue dots represent the number of tweets that included the keyword 'earthquake' after the Mexico earthquake on 20th March 2012. The yellow line is the trend line that shows the spike and the drop after the first hour.

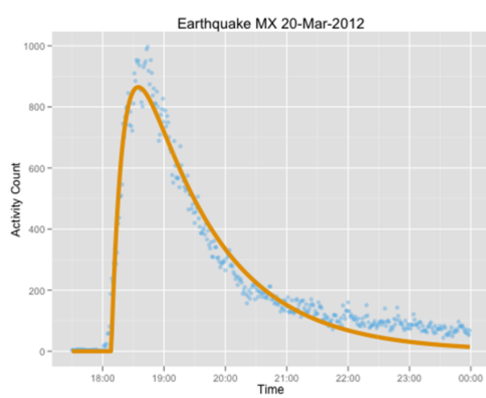


Figure 9: People's response for Mexico earthquake in Twitter with #earthquake hashtag

However, this drop in intensity varies based on the nature of the event. When an event happens unexpectedly, Twitter users inform their followers or just spread the word about that event. Whilst users who were informed late continue to share information, the overall volume of tweets reduces.

In terms of the content or the source of the tweet, it can range from people on the ground to those living far away who want to share their concern. A user in the ground may write "Slightly dizzy after being shaken around by the Chengdu earthquake for several hours now,", while a user who may or may not be near the location might write “there is a 7.9 #earthquake in #Chengdu”. The update can be in the form of tweet, retweet or reply. The tweets may contain keywords or hashtags related to the location or just generic information. However, what is common is that during such disruptive events people tend to flock to social media and share information, creating a massive spike in information regarding that particular event.

On the other hand, events that are anticipated have a different curve. Perhaps as the people are familiar with the time and date of the event, only few people start talking about it earlier and most talk about it only when the events occur. This produces a bell curve for events such hurricane Irene (Hendrickson, 2012). That is why slow moving event such as a flood, the pattern of Twitter usage is similar to a hurricane rather than an earthquake. As it was seen in Queensland flood, people tend to share tremendously at the very beginning and the rate of sharing drops afterwards (Bruns, et al., 2012)

In conclusion, there is a large volume of social media data that gets generated in Twitter after a natural disaster. Moreover, it also gets generated very quickly. Therefore in theory, by harvesting those streams it is possible to identify disaster relevant information that is appropriate for action in times of disaster. The task for emergency managers is to identify relevant information from this dataset quickly, but due to the volume and speed of the data the is created, this task becomes extremely challenging.

Context and noise The challenges are not just limited to the volume and speed of social media output, but also to group a tweet in appropriate context. This is because it is possible to read different meanings from words depending on the context. For example, same word ‘shake’ can mean earthquake or a milk shake based on the context it is used. This is termed word-sense disambiguation (WSD) and is a known problem in computational linguistics (Banerjee & Pedersen, 2002) as well as in Twitter research.

However, in the context of Twitter Huston, Weiss and Benyoucef (2011) have argued that identifying the context of the conversation can eliminate this disambiguation as the words are meant to represent the context. Furthermore, using words with hashtags can help to eliminate that issue because with the hashtag, people are putting their tweets in the context of a wider ongoing conversation. However there has been cases of misusing hashtags for promotion (knowingly or unknowingly), and for spam.

Therefore when tweets are processed in real time the context and relevancy identification poses a challenge. Some of the ways Twitter researchers have addressed this has been explained in detail in the methodology chapter.

Veracity Credibility of information is an issue in Twitter (Castillo, Mendoza, & Poblete, 2011). In the seminal paper “Can we trust what we RT”, Mendoza et al. (2010) examined if it is possible to differentiate real information and rumour in Twitter. The authors found that rumours or fake information tend to have more provocative tweets rather than descriptive or seeking help based tweets. Similarly, Gupta and Kumaraguru (2012) identified 50 different variables such as tweet length, whether the tweet included a URL and the number of followers of the user who tweeted it, to rank tweets based on their relevance. However the problem with automatically classifying tweets based on their meta-data alone is, it may miss the context the tweet is in.

According to Chen and Sakamoto (2012) people are more likely to spread information via retweet if they can relate to the situation. They are also more likely to spread negative information (such as death toll, building collapse etc.) than positive information during disaster. This might be because negative information has more attention grabbing potential than positive information (Pratto & John, 1991). Therefore updates such as “the road is ready to be used” are less likely to get retweeted than “5 new deaths in Toowoomba”. Since these tweets are usually not verified at the time they are sent, they potentially contain a lot of irrelevant information for emergency services and can pose problems of reliability, authenticity and usefulness (Mendoza, et al., 2010).

The complexity of separating credible information from rumour therefore remains extremely challenging. Although studies have been conducted in the area of deep machine learning that focuses on automatically identifying credible information it is still not possible to automatically identify credible information (Arel, Rose, & Karnowski, 2010). This thesis therefore does not engage with the verification of information because the challenges that come with veracity are beyond the scope of this thesis.

Temporality The longevity of a tweet can vary depending on many factors (Bruns, 2011). Although the design of Twitter encourages quick status updates, many tweets that appear important gets passed on during a disaster (Starbird & Palen, 2010), and in some cases long after the validity of the tweet is expired (Maxwell, Raue, Azzopardi, Johnson, & Oates, 2012). For example, in the 2011 Queensland flood a tweet asking help from other users to collect animals from a RSPCA centre that was being affected by the flood was highly retweeted and many volunteers drove to get the animals out. However, long after all the animals were gone and flood water was already inside the facility, people were still coming, as a later tweet from the RSPCA advising that all animals were already removed was not as highly retweeted (Cheong & Cheong, 2011).

Identifying such temporal information remains a problem for Twitter research with regards to natural disasters (Cataldi, Di Caro, & Schifanella, 2010). Although time-stamp metadata can be used to identify the temporality of a tweet, people can copy from another person’s tweet and paste it, making it difficult to use in a real time situation. As incorporating temporality increases the complexity, this thesis does not engage with the temporality of information from Twitter.

2.3.9 Emerging from Twitter related literature

After addressing why Twitter was chosen for this research, this section reviewed three key areas of literature related to Twitter usage in a disaster situation: activities that are Twitter centric that might be unique to the platform, theories that can provide an explanation of the way users use Twitter, and the key challenges of identifying information from Twitter.

From the discussion it can be seen that after a natural disaster people use Twitter to seek information related to their family members or the area their family lives in, and they update information about their surroundings by posting tweets, images or other media items. However, a large number of users, who are not in the affected area may also post simultaneously. Sometimes they retweet, sometimes they post original tweets offering sympathy to the disaster affected area.

This act of tweeting on a massive scale provides both opportunities and challenges for emergency services. On one hand, these updates regarding surroundings provides actionable information for emergency services, but on the other hand, it may get lost easily in the large volume of irrelevant but fast appearing tweets. Other challenges such as the high visibility of rumours and outdated information also poses additional problems in gathering disaster relevant information.

Overall, an extensive amount of research has been conducted that looks at what is being said in the tweets and how these can be filtered to identify relevant information. Theories of collective behaviours have also been used by researchers to investigate how the techniques of identifying relevant infromation can be improved. Certain theories such as contagion theory suggest that retweets are likely to be not useful. Convergence theory discusses why Twitter users are likely to adopt a dominant hashtag to be part of the on going event and complex adaptive systems theory suggests how users might be integrating new features and evolve the way they had been communicating. The next section combines the literature summaries from both sections, natural disasters and Twitter, to identify key challenges and opportunities for this research.

2.4 Summary

There is a body of literature that has analysed Twitter data from various natural disasters around the world to suggest that there are possibilities and challenges in finding relevant information for emergency services from Twitter (Acar & Muraki, 2011; Mendoza, et al., 2010; Verma, et al., 2011; Vieweg, Hughes, Starbird, & Palen, 2010).

From an opportunity perspective, Twitter helps people to mobilise themselves to assist others, allows first responders to communicate between themselves and acts as a potential information source and venue for dissemination. These actions are similar to the information needs identified by the emergency services, including information related to the community, information regarding which area has been most affected and feedback on the relief effort (Bodenhamer, 2011; Hall, 2007; Reynolds, et al., 2002; UNISDR, 2013).

However, the challenges of finding this information are many. From the literature it can be seen that most of the tweets related to disasters contain information from outsiders that include sympathy, retweets of existing reports, and misinformation or outdated information – all not what is regarded as relevant by emergency services.

Therefore, although research has already been conducted on finding information from Twitter, there is a gap in identifying information automatically that is relevant for emergency services after a disaster. In order to do that this research uses a mixed methods approach by combining quantitative and qualitative research tools. In the next chapter the methodological approaches are discussed in detail.

Chapter 3: Methodology

The previous chapters, the Introduction and Literature Review, have identified the overall information needs of emergency services and the potential and challenges in finding this information from Twitter. This chapter discusses various methodological approaches used in identifying specific information from Twitter before outlining the research design used in this dissertation. The theories and frameworks described in this chapter broadly fall under the computer science discipline, the third component of the research domain described in Figure 3.

This chapter is structured into three sections. The first section discusses various data types and how Twitter data is collected. The second section discusses the methods of analysis and tools for collecting data. The third section addresses the research design that describes the flow of the research, followed by a description of how results from the experiments were evaluated in this research.

3.1 Deep Data, Surface Data and Big Data

To understand computational methods in social science, it is necessary to understand what types of data social science researchers collect. Manovich (2011) proposes that there are two types of data. One is surface data, which stands for data collected from many people but where the collection method limits it to surface level information. The other is deep data, which is more in-depth and often from a small number of participant. Both of these are build on variations of two well-established paradigms known as quantitative and qualitative research.

Deep data is about gaining a deeper understanding of a very small sample of data (Manovich, 2011). Various branches of humanities and social sciences use the deep data approach to understand what is going on with the subject matter. Most of the time 'why' questions tend to shape these type of research. This type of research tends to use qualitative methods such as interviews, participant observation and focus groups to gather data on an event.

Surface data on the other hand is used to find a pattern by analysing large datasets where most things are converted to numbers and then grouped based on those numbers. Computer science, statistics and economics tend to use surface data. In these type of research the questions ask 'what' rather than why. Most of the time, these research cover large sample of the population, as they do not require significant time investment from the participants.

Big data on the other hand can combine both surface and deep data. Unfortunately there is no agreed definition of Big Data. Even the widely cited article by boyd and Crawford (2012) vaguely defines big data as "a cultural, technological, and scholarly phenomenon". Mayer-Schönberger & Cukier (2013) defines big data as an ability to crunch and analyse a large volume of data, to draw astonishing conclusion from that data (Mayer-Schönberger & Cukier, 2013) but do not define what consists of the large volume of data. Therefore in a traditional sense a dataset of big data has three characteristics or three Vs; volume, velocity and variety. This type of data is meant to be beyond the scope of traditional database storage and requires a different approach to indexing and retrieving information stored in the database. Even though the original term 'big data' stands for large data set, and tweets are made of 140 characters, the reason Twitter data falls under the big data category due to the collection of information and the frenetic pace at which it gets generated. Therefore 500 tweets is not considered big data but 500 thousand tweets, which is a common number of tweet after a natural disaster can be considered as big data. It is necessary to note using such an example is problematic because situation of considering 500 thousand tweets as big data is likely to change as amount of data gathered continues to increase.

Although a standing criticism of Big Data is that it is only surface data (Uprichard, 2013; Kitchin, 2014), computational social science researchers have been engaging with Twitter and big data is to understand human behaviour on a large scale (Broniatowski, Paul, & Dredze, 2014; Wang, Chen, Thirunarayan, & Sheth, 2012; Zikopoulos, Parasuraman, Deutsch, Giles, & Corrigan, 2012). Understanding human behaviour has traditionally been part of the qualitative or deep data approach, as it was not possible to gain deeper understanding about someone's life when collecting information through quantitative collection methods. With big data and social media this is changing, and in doing so is allowing researchers to collect large scale data about human behaviour including contextual human experience and analyse it using both quantitative and qualitative methods (Tufekci, 2014).

In addition, for the purpose of many social science researchers big data also acts as a starting point to identify meaningful pattern that can be analysed further. Using abductive reasoning on big data sets researchers looks for patterns in order to form their hypothesis before formally proceeding with deductive theory construction and inductive empirical testing (Dixon, 2012).

Therefore, even though big datasets create problems in terms of storage and accessibility, and often requires new ways of dealing with the data, big data has also been changing the way researchers understand and experience knowledge (boyd & Crawford, 2012; Lavalle, Lesser, Shockley, Hopkins, & Kruschwitz, 2011). These large datasets have given researchers the ability to find information ranging from medicine to astrophysics that they were unable to find before. Another reason this area of research has risen to prominence among social scientists is the ability to understand human behaviour through social media. As increasingly more people join and share information and day to day life in social media, social media is becoming an important tool through which to gain more insight into how people behave.

In conclusion, Twitter researchers have used the Twitter dataset for various purposes. Some researches have used only deep data through qualitative methods, some has used surface data with quantitative methods and some have used big data with quantitative or mixed methods. After discussing what data points can be gathered from Twitter, research methods are discussed in this chapter under methods for analysis section.

3.2 Gathering Twitter Data

It is necessary to consider the question of ethics before gathering Twitter data. In gathering data from Twitter, most, if not all of the tweets that are gathered using API comes from publicly available tweets. Therefore, from a technical point of view there are no ethical issues in gathering Twitter data. However, tweets are expression of users and when users expressed their thought and emotions via tweets they may not have intended their tweets to be gathered in a dataset. Therefore when gathering datasets from tweets this issues needs to be carefully considered.

However, in this case the dataset was gathered around hashtags and keywords related to a major natural disaster and details of the dataset is discussed at the end of this chapter. It can be justified that since users tweeted with that specific hashtag or keyword in their tweet, they deliberately meant the tweets to be visible to other members of the hashtag as the hashtag is a crisis hashtag and contribute to the on going crisis discussion. Furthermore this research is aimed at finding patterns in the tweets rather than focusing on the content of each tweet. This removes the focus from the contribution of individual user and looks at the overall response pattern of the crisis and how a meaningful contribution can be obtained from these patterns. Therefore the possibility of this research and the tool developed from this research being harmful to individual is minimal. In addition, this project has also received ethical clearance from QUT to conduct the research.

In order to use Twitter data for research, after considering ethics, next step is to collect the data (Woodford, Walker, & Paul, 2013). However, due to availability of many data points in Twitter (Broniatowski, et al., 2014), as well as limitations imposed by Twitter (Puschmann & Burgess, 2013), one needs to be selective about what type of data to collect. In order to understand what can be collected that is potentially be useful for emergency services, this section first addresses the relevant components of Twitter for emergency services, followed by a discussion on Twitter data and metadata. This then leads to a discussion on various data sources and limitations. The section then concludes with reasoning for choosing the specific method for collecting data used in this thesis research.

3.2.1 Twitter data

The first element of gathering Twitter data is to understand the building blocks of Twitter. Although Twitter has various components, tweets and users are the two key items that are visible to any Twitter user (Twitter, 2013). The following section therefore firstly discusses tweets. This is then followed by a discussion of users. Although this research focuses on tweets, detailing the technical side of a user account can assist in understanding the building blocks that can be used to identify disaster related information.

Tweet A tweet is the most basic building block of Twitter (Twitter, 2013). This is what people read when they are posted in Twitter. A tweet can contain any language supported by computers (e.g., English, Chinese, Arabic), embedded images, website URLs, hashtags, and @replies. Each tweet is limited to 140 characters. They can also include emoticons (funny faces, sad faces etc.). Tweets are also referred to as status updates. Any tweet can be embedded into another website, other users can reply to that tweet, they can also favourite that tweet, or unfavourite it. Only the user who composed the tweet can delete it. Figure 10 shows a sample tweet related to a crisis situation where a Queensland based regional council is advising their residents to evacuate an area.

Figure 10: A Sample tweet related to a crisis situation

Figure 10 demonstrates another Twitter practice, the “MT” or ‘modified tweet’.’ This marker is inserted by Twitter users to indicate that the tweet was not composed by them

Although this does not reduce the importance of the tweet, it is necessary to understand the various types of tweets and the contents users can create namely; original tweet, retweet including modified and quoted tweet, @replies, hashtags, URL and media.

Original tweet An original tweet is usually the 140 character long message composed by the user from their account and is viewable publicly. For example in the sample tweet in Figure 10, the original tweet was from the account QPSmedia, who wrote the message about Moreton Bay Regional Council advising residents to evacuate. During natural disasters many people who are on the ground share their current situation in the form of original tweets (Starbird, Muzny, & Palen, 2012). It could be describing their situation (Bruns, et al., 2012; Hughes & Palen, 2009), posting photos of their surroundings (Boulos et al., 2011), venting frustration about their environment, or wondering how others are doing. In disaster situations original tweets are not only composed by people who are on the ground, people in other places may post original sympathetic tweets such as “pray for Haiti” (Smith, 2010) or “pray for Queensland” as well. Similarly, people from far places may post original tweets that contain keywords such as “help people in Queensland” which, although is a demonstration of good heart, is not useful for emergency services.

Retweets (RT) Redistributing another user's tweet to their own followers is known as a retweet and Twitter users can do that via retweet button or manually but putting "RT" in front (Bruns & Burgess, 2011a). Manual retweeting has always been practice of Twitter users, however when the retweet button was introduced in 2009 (Kwon & Han, 2013) it became a common practice, partly due to the increased ease, and partly because the nature of Twitter encourages sharing.

Significantly for this research, retweets often count for a large volume of Twitter activity in a natural disaster. In the ARC Centre of Excellence for Creative Industries and Innovation (CCI) floods report Bruns, et al. (2012) found that the number of retweets were often higher than original tweets. After the Japan earthquake in 2012 the number of retweets were 20 times more than normal retweet rates (Miyabe, Miura, & Aramaki, 2012). While it amplifies the visibility of tweets, a large number of retweets contain media based information that is of limited use by emergency services. Due to their lack of relevance for emergency services, retweets were the first element that was filtered out in this project. The method of doing so is described in chapter 5.

@ replies Replies to another user's tweet are marked with @reply. This @reply does not necessarily have to be a reply to a status update, it could be a user attempting to reach another Twitter user. Users can place a dot (".") in front of the @ to ensure that this @reply is a public message that is broadcasted to all of the user's followers. This form of sending a public message is often seen in political and crisis communication. Replies usually suggest conversation, but during a disaster it can be an attempt to reach a user. As observed by Bruns et al. (2012), about 200 replies were sent to the twitter account of the Premier of Queensland although they were not meant to start a conversation, but rather to alert or to report a specific situation. In terms of conversation replies, the number of genuine replies to a specific user in a natural disaster suggests a higher visibility of that user's tweets compared to others. Emergency services can therefore use replies to identify influential or visible users on whom they can focus to get more information.

Hashtag (#) In the previous chapter hashtags were introduced as a user generated communicative feature. Whilst Chris Messina is credited as the inventor of the hashtag for Twitter, it became mainstream during the San Diego forest fire in 2007. Citizen journalists used hashtag #sandiegofire to communicate about the fires (Zak, 2013). Since then, hashtags have been used in many different areas from business, politics to crisis situations such as natural disasters, riots or plane crashes (Cullum, 2010; Glasgow & Fink, 2013; Lin, Margolin, Keegan, Baronchelli, & Lazer, 2013; Tsur & Rappoport, 2012). In this research the data was collected using specific hashtags, as is explained later in this chapter.

URL URLs shared with Twitter during annatural disaster generally consist of additional information (Bruns, et al., 2012). During the Queensland flood, the majority of URLs shared were either image services (as Twitter did not have their own embedding image option) or links to government website and traditional media websites. From an emergency services point, this may not provide them with additional information, although it can highlight new community sites that are gaining popularity, as was seen in the Thailand flood in 2011 (Terpstra, de Vries, Stronkman, & Paradies, 2012).

Media Images shared during natural disasters can be of immense help to emergency services (Terpstra, et al., 2012). At the same time, fake images can be problematic, and to tend to appear a lot during natural disasters (Gupta, Lamba, Kumaraguru, & Joshi, 2013). Users can embed media such as an image or vine video along with the tweet. This can be done by attaching the image in Twitter itself, or via various third party apps that support Twitter. However, while an image contains various meta (EXIF) data, when it is uploaded to Twitter, the metadata is stripped off to ensure it is not trackable (Harvey, 2014). While this protects the privacy of the user and makes the user non identifiable, it also eliminates the possibility of emergency services to identify if the images are directly taken on a camera or have been modified via Photoshop.

Overall, as can be seen from the Twitter research cited in this section, a tweet contains a range of data points that can be used to identify various patterns.

Researchers have used these data points, either singly or in a combination, to address specific questions. Which of these components can be used to determine if a tweet is relevant for emergency services is addressed in the next chapter.

The other key component of Twitter that is often researched is the users. Even though user based features, such as a count of tweets or followers and following were not used in this research, detailing the building blocks of the user can increase understanding about this research project. The remainder of this section therefore discusses various user specific components and the ways these have been used in Twitter research.

User Profile The user profile consists of various attributes about the account holder. Although it is meant to be a person, the account holder can be an automated bot such as earthquake bot or a spam bot. A twitter profile contains various data that can be useful in disaster purposes. Similar to tweets, the user profile has both visible information and invisible information. This section discusses the markers that are useful for emergency services during natural disasters to extract useful information.

Figure 11: A sample profile page of Queensland Police Media Unit

Username and accounts As can be seen in the above profile (Figure 11), there are two named units. On the top is the real name and the other is the @username. Usernames are sometimes also called the user handle. The username appears in the URL and is unique. The real name indicates who the account holder really is as a person or organisation, however there is no requirement to use a real name in Twitter. The username can have 15 characters and the real name 20. Both the username and the real name can be changed at any time. The only difference is, as the username is unique, changing a username requires that the new username is not in use by anyone else. The real name on the other hand can be changed at anytime without having to worry about duplicates.

From an emergency services point of view, a real or user name can assist in identifying if the information is coming from the general public or from a media organisation. In addition, if the name suggests that it is an automated system (e.g., Figure 12), it could mean that the user is updating their status from sensors, which can be used by emergency services. Overall, both the username and real name can be useful for emergency services to identify who the user is.

Figure 12: A sample profile page of an automated bot

Description In this space Twitter users briefly describe themselves. In general people tend to explain briefly what they do. Official accounts such as the Queensland Police Service (Figure 11) may use this to describe more important things as well. Official bots (bot-assisted human or human-assisted bot) tend to have a written description indicating that they are automated accounts (Figure 12). Wagner et al. (2012) suggest that the description is a key attribute to identify the topic expertise of the user. Thus, if the user is an expert in disaster related information, it is likely that they may have this detail about themselves written in the description. By extracting such information, emergency services can identify key personnel and get informative tweets.

Count of tweets, followers and following An additional part of the user profile is the count of followers and following. A follower count shows how many other accounts follow this user and the following count shows how many other accounts this user follows. Generally a popular figure such as celebrity, media or important accounts have a very high follower count, while they do not follow a similarly high number of accounts. Compared to that, a new user who is not famous in the offline or real world, will have limited number of followers and following. On the other hand, active twitter users may have a close ratio of followers and following counts, having hundreds on both sides. A high follower count from a user account can be an identifier of credible tweets, since users with a high follower count are less likely to damage their reputation by sharing false information (Morris, Counts, Roseway, Hoff, & Schwarz, 2012). These type of users with high follower counts can belong to the group the Reynolds and Seeger (2012) have argued are 'leaders' who tend to post important information, and in case of incorrect postings, tend to correct themselves. For emergency services, such users could be useful for identifing breaking news.

The count of tweets indicates how many tweets a user has sent out and can be an indicator of a novice user or 'elders' (Reynolds & Seeger, 2012). Elders are the type of user who has been active before but stopped being active. They are likely to have large gaps between tweets but they could jump back if the situation demands for it. These users are likely to be familiar with various the twitter terminologies described earlier. Novice users however could be those who have heard of the benefits of twitter during a disaster and have just signed up to get or provide information (Vivacqua & Borges, 2012). In all those cases, tweet counts and time of tweet can be a useful marker for emergency services.

Profile image Profile images are an important part of a user's expression of identity. By default Twitter provides every user with an 'egg' image. The account holder can upload a preferred image to replace the egg. The usefulness of profile image is it visually distinguishes new users with older users without looking at other data sets. Even when analysing it programmatically, if the user profile is an egg and the user's tweet count is low, it might suggest that this is a new user. With regard to emergency services information, if such a user has started to tweet about the location it could be that the user has just signed up to update about the disaster.

Verified Sometimes a blue verified badge (a tick sign) appears in the top right portion of user profiles. This is to establish the authenticity of the account, and is done for highly sought after users in key interest areas. These areas include celebrity (e.g., sports, music, acting), political and governmental figures or organisations, media, religious leaders, and well known businesses and business leaders.

The relevance of the verified option is that, it is almost impossible for a normal user to be verified and that a tweet from verified user may be expected to be retweeted a lot. Furthermore, such an account could belong to other emergency services from other government areas or local areas and thus providing relevant information. In addition, these users could be 'leaders' in another field and they may take an interest in the disaster outside their usual role (Tonkin, Pfeiffer, & Tourte, 2012). Thus the verified user tick is a key marker of information verification, but not necessarily for information gathering for emergency services purposes.

User ID Although every user has a user ID number, it is hidden and often the user is not aware of the number. The benefit of knowing this number is that, unless the user deletes the account, the number does not change. Therefore, even if the user changes their username or real name, it is still possible to find information about that user by using their ID number. Such information can assist in identifying users who have been active in previous natural disasters. Although there is no guarantee, it is possible that the user who was active in a previous disaster will also be active in the current disaster. And in case they have changed their user handle (username), they are still identifiable through Twitter.

Location data There are two ways a user can provide their location. The first is by setting their location in their profile. Second is when a user enables geo location, the geo enabled field gets populated with geo location data. This data then can be used to identify where the user is located. This is a very powerful feature and can be useful during crisis. However, due to various reasons such as high battery consumption of geo location features and privacy concerns, people are often unwilling to share their geo location data. Thus other ways are needed to identify users and their locations. An alternative option used by researchers is to convert the time zone to a location.

In conclusion, Twitter has many building blocks that can be used by emergency services to find relevant messages. Although both tweets and users were discussed in this section, in this project only tweet data was used. The main reason for only selecting tweet data is that including user data would have increased the scope of the project immensely due to various challenges associated with user data. In addition, when the data was gathered for this research only tweet data and not user data was collected. Using the latest user information on archived data may also mislead the direction of the research. Therefore only tweet data was used in this research.

Nonetheless, each tweet contents a lot more information than what is visible through the Twitter feed. In the next section this invisible data, or metadata is discussed in further detail.

3.2.2 Twitter metadata

So far the discussion about Twitter data has been around what can be seen from Twitter. Metadata on the other hand, is structured data provided by Twitter that allows access to feature objects that may or may not be visible directly from tweets. According to Dwoskin (2014) there are 150 different metadata associated with each tweet, which includes commonly visible metadata such as retweet counts and hashtags, to metadata that can only be accessed through an API, such as location metadata. A number of studies have used Twitter metadata to identify key moments in communicative activities because metadata can go beyond the contents of the tweet to identify important information (Burks, Miller, & Zadeh, 2014; Leetaru, Wang, Cao, Padmanabhan, & Shook, 2013). This section discusses the opportunites and challenges associated with metadata, and discusses the different approaches researchers have used to access the metadata in order to identify disaster relevant tweets.

Burks et al. (2014) found that the occurrence of location metadata in the earthquake area in Japan was almost representative of the seismic data reported by geological services. Researchers have also analysed location metadata to identify areas affected in real time (Davis Jr, Pappa, de Oliveira, & de L. Arcanjo, 2011; Kinsella, Murdock, & OHare, 2011). Based on the findings of this research it can be suggested that the identifying location is a crucial factor in a disaster (Davis Jr., et al., 2011), and that metadata such as location and time zone are useful for emergency services to identify disaster relevant information (Yin, Lampert, Cameron, Robinson, & Power, 2012).

However, extracting information such as location from Twitter can be challenging. First of all, most people do not enable geo location data in their tweets due to various reasons such as privacy and excessive battery consumption on mobile devices (Hale, Gaffney, & Graham, 2012). Furthermore, images that are attached to tweets are stripped of their GPS and other metadata (Harvey, 2014), making it impossible to extract location data. Since location metadata is collected based on the device's GPS location, it is dependent the user switching on their location. Since only two percent people keep their GPS switched on (Hale, et al., 2012), emergency services cannot rely on location metadata.

To address this limitation, MacEachren et al. (2011) searched for extracting location information from tweets to find disaster related Tweets. However, extracting location names is a complex information retrieval task (Jung, 2012; Li et al., 2012; Liu, Wei, Zhang, & Zhou, 2013; Nadeau & Sekine, 2007; Ritter, Clark, & Etzioni, 2011). This is because, for example, street names are often based on people's names, making it difficult to differentiate. In addition, many roads around the world share the same names. An Oxford Street could be in U.K., U.S., Australia or any other country. There are 10,893 streets named as Second Street in the U.S.A. alone. Thus finding exact locations is problematic (Finin et al., 2010; Jung, 2012; Liu, et al., 2013), and because of this named entity identification remains an active area of research (Klein, Smarr, Nguyen, & Manning, 2003; Yin, et al., 2012).

Such problems can potentially be addressed through hashtag based location (Huang, Liu, & Nguyen, 2015). Recent studies have found that Twitter users sometimes use location names as hashtags. Identifying such information can help emergency services to identify tweets that are related.

Another reason to extract metadata from tweets instead of relying on invisible metadata is that filtering information based on metadata can lead to false positives that a human would be able to easily identify. An example of this can be seen in the study conducted by Gupta and Kumaraguru (2012) and as was demonstrated in Figure 9 in the Veracity sub section of the Literature Review. Only considering underlying metadata can allow a tweet or image that is satire to be counted as credible. One of the reasons for this is that, when using metadata alone, the tweet is taken out of the context of what is being said. Thus, counting only on Twitter metadata might be a useful tool to get an overall summary or pattern, but is less helpful to identify individual tweets where a user is asking for help.

In conclusion, researchers have identified that metadata contains information that is potentially relevant in disaster situations. However relying only on what is provided by Twitter is problematic and is more useful for understanding patterns than identifying individual tweets. On the other hand, metadata that is extracted from tweets, such as location or image, can be useful for emergency services and are considered in this thesis.

3.2.3 Twitter data and metadata source

Having discussed what relevant information for emergency services can be collected from Twitter, this section addresses the sources that Twitter data and metadata can be collected from. This is because despite tweeting activities are done via Twitter and the tweets are mostly public, accessing all tweets is restricted by Twitter (Puschmann & Burgess, 2013). A commercial license is required to access both the full dataset, known as 'firehose' and a 'decahose' which incorporates only 10% of all tweets (Leetaru, et al., 2013). The alternative is free access to Twitter API data, but the tradeoff is it returns only 1% of the Twitter contents.

Source	**Sample returned**	**Historical Data**	**Cost**	**Common Export Format**
Twitter website	As much as user can see	Undefined - may return historical data	Free	Manual reading
Twitter Search API (part of REST API)	Approx 1500 tweets	One week	Free	json
Twitter Streaming API	1% of Twitter data	None – live data only	Free	json
Data reseller (Gnip -acquired by Twitter)	Full twitter firehose	Complete Twitter archive from Mar 2006	Subscription starts at $500	json, HTTP Streaming, WebSockets
Data reseller (DataSift)	Full Twitter firehose (available till Aug 2015)	3+ years of Twitter data	Subscription starts at $3000 per month	json, HTTP Streaming, WebSockets
3rd party vendor (radian6 salesforce, crimson hexagon)	Full Twitter firehose	Depends on the vendor	Starts at $500 per month and increases per volume	CSV or other commonly used format
Texifter	Full Twitter firehose	Depends on the vendor	Starts at $30 per 100,000 tweets for 1 to 500,000 items	CSV

Table 3: Twitter data sources

Table 3 shows the data sources available from Twitter, along with the amount of samples they return, the availability of the data, cost and export formats.

As it can be seen in Table 3, the free option to collect data from Twitter is only available from Twitter itself via API or by reading Twitter feeds manually and copying it from the search results in the website (Kim et al., 2013). Although reading it manually is by far the simplest option, the challenge with the manual approach is, as highlighted in the previous chapter, that when a natural disasters happens the volume of tweets is extremely large. For example, during the 2011 tsunami in Japan there were almost five thousand tweets regarding the disaster every second (Acar & Muraki, 2011), and during the Mexico earthquake in 2012 there were more than 800 thousand tweets in first half hour (Hendrickson, 2012b). This large volume of data makes reading and identifying important tweets an impossible task during a natural disaster. Therefore the preferred choice of Twitter researchers is to collect data by using the Twitter API (Perera, Anand, Subbalakshmi, Chandramouli, & Ieee, 2010), as the paid options of using data resellers can be costly (Kim, et al., 2013).

Of the two types of API detailed in Table 3, the most commonly used in Twitter research is the streaming API (McGuinness, 2013). This is because streaming API focuses on completeness, compared to a focus on relevance of the search API (Twitter, 2012). The relevance search is based on direct and non-recurring queries. For example, searching for “my friend” with the search API will return a result that contains top tweets ranked by Twitter’s own sorting algorithm. These top tweets over represent the central users and do not show all the tweets (González-Bailón, Wang, Rivero, Borge-Holthoefer, & Moreno, 2012). Furthermore, there is a limit on how many API searches can be performed. The rate limit of search API is related to how many calls are made, which in a disaster situation often reaches the limit very quickly. At present the API search rate is limited to 15 minutes intervals, and only delivers 180 to 450 tweets depending on authentication type (Twitter, 2015). Since during natural disasters thousands of tweets appear every second, being able to search for only 180 tweets in 15 minutes limits the amount of data researchers can work with.

On the other hand, streaming API is designed for data intensive applications that require a real time sample of Twitter data. Thus streaming API allows for large quantities of keywords to be specified and tracked, retrieving geo tagged tweets from a certain region, or to have the public statuses of a user set returned. Once a keyword, hashtag, username or other search criteria is determined, Twitter will deliver tweets that match those criteria (McGuinness, 2013). Given that in a crisis situation, finding tweets that require an action such as providing help or information is more important than finding a top tweet, the standard practice in Twitter research is to use the streaming API.

However, there are two key issues with streaming API searches. Firstly, it only delivers 1% of tweets (also know known as Spritzer) (Conover et al., 2011) for free. The second issue is that the streaming API does not provide access to past or historical data. Therefore it is not possible to collect data based on a hashtag that is stored on Twitter servers. Streaming API searches only collect data once that hashtag is added to the tweet collector tool, and only from the incoming feed.

The concern about a 1% data sample is the question of representativeness. One of the common criticisms of utilising only 1% of tweets is that as 99% of the tweets excluded, that streaming API data cannot be used for research to make generalisable claims (Gerlitz & Rieder, 2013). To address this issue, Morstatter et al. (2013) compared firehose data (100% of Twitter data) with the 1% of data collected from streaming API and found that in many cases data gathered from the streaming API contains a sufficient sample. In addition, Morstatter et al. (2013) found that there is an insignificant difference between the 1% of data and randomly choosing a dataset from firehose.

The area where firehose output was significantly better than streaming API was in the discovery of new hashtags (Morstatter, et al., 2013). However it has been argued that hashtags are a self-selecting tool which Twitter users tend to include when they think this will contribute to the discovery of related information or that their contribution is related to the hashtag (Anagnostopoulos, Kolias, & Mylonas, 2012; Cullum, 2010; Tufekci, 2014). Thus although misuse of hashtags is common in

Twitter conversations, and is one of the biggest contributor of noise, the dominant hashtags surface quickly and tends to be followed by other users (Ma, Sun, & Cong, 2012). Once the relevant hashtags have been established, following the hashtag will likely generate conversation related to the topic (Bruns & Burgess, 2011b). Since this research is not trying to identify a breaking event through a tweet, it is not necessary to find all hashtags to identify which is the most dominant hashtag.

In conclusion, even though streaming API has various limitations, the benefits of being free outweigh the challenges associated with it. In the section where sampling of Twitter data is discussed, some of the ways these challenges can be overcome are explained. However for the purpose of this project, streaming API was deemed sufficient because emergency services often do not have the budget to purchase expensive social media data for long periods of time. Furthermore with firehose, the amount of data generated is large and would therefore also require extensive computational resources (Woodford, et al., 2013). Once again it is highly unlikely for emergency services to have such resources. Therefore for the purpose of this project, streaming API was used and any tweet that used hashtags and keywords prior to adding it in the list of the tools were not recorded. In the next section some of the tools used for gathering Twitter data are discussed.

3.2.4 Data gathering tools

In order to collect tweets and other metadata from Twitter using streaming API, researchers have used a range of tools including open source tools such as YourTwapperkeeper (Burgess & Bruns, 2012; Larsson & Moe, 2012) and DMI-TCAT (Borra & Rieder, 2014; Gerlitz & Rieder, 2013), or commercial tools such as Topsy (Thaiprayoon, Kongthon, Palingoon, & Haruechaiyasak, 2012). A brief list of free and open source tools that can collect large amount of Twitter data in an exportable format are provided in the Table 4. This list is not intended to be all encompassing, as constant changes in the way Twitter works means new tools are continually developed.

Tool	Description	License
Chorus Analytics	Combined in two parts - TweetCatcher searches streaming API for keywords and hashtags and TweetVis, visualises the streaming contents.	On request, Free
Discovertext	Cloud based collection and analysis solution from texifter. Uses streaming API for free version and Gnip for paid version.	Free and Paid
DMI-TCAT	Similar to YTK, DMI-TCAT runs on a web server and the data captured can be exported in formats such as CSV or GEXF (Borra & Rieder, 2014). In addition to collecting data it can also analyse and provide visualisations of that data.	Free
Follow the Hashtag	Web based search tool but only allows 1500 tweets to be captured at one time. If searches require more than 1500 tweets, searches must be repeated after a while	Free (in beta)
Sodato	Newly developed data collection and analysis tool that allows connections to Facebook and Twitter to collect data on a large-scale.	Free (in beta)
TAGS (Twitter Archiving Google Spreadsheet)	By using Google spreadsheet as the database, this tool allows a quick checking of keywords. It is popular for testing some keywords but is less practical in a disaster situation as the database is not get updated in real time	Free
Topsy	By using firehose of Twitter, Topsy provides a real time analysis of what people are saying about keywords. It also provides social analytics and a trend application as part of the package. Apple bought this service in late 2013.	Paid
Tweet Archivist	Allows tracking of data from streaming API once the keyword or hashtag is inserted. Pricing starts from $15 a month and allows archiving of three entries	Paid
Twitonomy	Creates a visual analysis of a specific keyword, hashtag or user. Allows exporting in multiple formats.	Free
twXplorer	In addition to archiving, it provides a visual analysis of recent tweets with identified terms. The most popular links and hashtags which appear in those tweets, and the most popular other terms which appear in those tweets are also included.	Free
yourTwapperkeeper	One of the oldest tools available for collecting data on Twitter. Formerly this tool was available via the organisation's website and anyone could use this to download tweets from the Internet. However as this was in conflict with the terms and services of Twitter, it was stopped. The company then published it as open source tool which people can download and install in their own server. For the purposes of this research this tool was used to collect the datasets.	Free

Table 4: List of off the shelf Twitter data collection tools

For this research, the datasets was based on the #QLDfloods hashtag and was collected using yourTwapperkeeper because most of the other tools mentioned in the tables above were not available at the time. The Yolanda dataset was collected by Qatar Computing Research Institute (QCRI) who has been collecting and mining social media data for various social and political events since 2012. To collect Yolanda dataset they used their own custom tool Artificial Intelligence for Disaster Response (AIDR), that has an initial component called 'collector' that is similar to yourTwapperkeeper (Imran, Castillo, Lucas, Meier, & Vieweg, 2014). The reason it was not listed in the table is because the collector tool is part of AIDR and does not work independently.

In conclusion, there are various data gathering tools available that can collect both Twitter data and metadata. Once these are collected, they are used for analysis using various methods. The following section therefore addresses various methods of analysing Twitter data, which includes the qualitative, quantitative and mixed methods approaches that are used in computational social science.

3.3 Methods for Analysis

From the discussions so far it can be seen that within the big dataset of Twitter, both surface and deep data can be found. Depending on the research question, a researcher can use either deep data or surface data approach to analyse Twitter data. Thus, usually Twitter research has been conducted with either quantitative or qualitative approach.

In a qualitative approach it is common for researchers to select a small set of Twitter data and study them manually to find meanings of specific tweets (Bunce, Partridge, & Davis, 2012). This approach is also known as a 'deep data' approach (Manovich & Gold, 2011). On the other hand, a quantitative approach looks to identify patterns from a larger set (Yin, et al., 2012). This approach of analysing surface data (Manovich & Gold, 2011) allows researchers to computationally identify emerging patterns (Lau, Li, & Tjondronegoro, 2011). This approach is useful for identifying breaking events such as new stories, tracking the whereabouts of a disaster, creating real time alerts or finding patterns in language (Verma et al., 2011).

This research applies a mixed methods approach, as a way of capitalising on the benefits of qualitative and quantitative methodologies. The research draws on what has been termed the 'computational turn' (Berry, 2011), which has focused on engaging digital technology in social sciences research processes. For Twitter research this mixed methods approach is useful as it allows researchers to expand their findings beyond the small qualitative sample (Choi & Park, 2013). This section discusses both the traditional and modern concepts of computational social science that use qualitative, quantitate and mixed methods approaches, and then explains how these approaches are utilised in this research.

3.3.1 Qualitative analysis methods

Even though computers and artificial intelligence have progressed tremendously in recent years, computers are still unable to identify relevant information as well as humans (Hovy, Navigli, & Ponzetto, 2013). Thus a number of studies have used human evaluation to extract initial features from a dataset (Jensen, Heidorn, & Richardson, 2013; Sabou, Bontcheva, & Scharl, 2012; Shore & Bice, 2012), before automating the process with quantitative approaches. In a mixed method approach, Twitter researchers have also used similar approaches of evaluating tweets with human evaluators in order to extract features that can be used with quantitative methods (Bontcheva & Rout, 2014; Go, Bhayani, & Huang, 2009).

There are many ways a human evaluator can engage and evaluate data qualitatively. As qualitative research tends to assess attitudes, opinions and behaviours, it is generally done via discourse analysis, content analysis, in depth interviews or focus groups, as well as close reading of tweets from key users (Marwick, 2013). However, for archived Twitter data, a preferred method is to do content analysis by creating a coding schema and use manual coding to evaluate tweets (Bruns, Burgess, Crawford, & Shaw, 2012). As this research also uses archived Twitter data, the subsections addresses the steps used in this method.

Sampling of data for analysis As qualitative analysis that involves close reading is usually done manually, it is a challenging task to take a large data set and engage in deep reading. Even though 1% of Twitter streaming API data appears manageable, it often generates hundreds of thousands of tweets, making it beyond the scope of human evaluation. Therefore before creating a coding manual or schema a sample from the archived Twitter data is drawn.

There are a range of ways in which a Twitter dataset can be sampled. For example, Bruns et al., (2012) applied a systematic sampling method and took a representative sample from the 2011 Queensland flood database (#qldfloods) by looking at every twentieth tweet from the #qldfloods dataset. Vieweg (2012b) used a random sampling method to select 1000 tweets from each dataset for coding. Bakshy et al. (2011) on the other hand used a stratified sampling method where they first filtered out spam tweets and grouped the tweets into several groups based on certain features. They then used the top groups for their analysis. The common characteristics of these methods are that probability sampling is the preferred sampling method, and it was this approach that was chosen for this project. The details of this method are explained later in this chapter.

Coding schema generation In qualitative studies, coding often refers to capturing the essence of a portion of language or visual data (Saldana, 2012). And finding this essence generally depends on the research question. For example, "Lots of new folks joining the Brisbane flood info center today. Join the online community at http://www.bnefloods.com #qldfloods #flood" can be coded as information sharing, URL, or a call for community building action depending on the question that is asked. If the intention is to identify the built-in metadata such as a URL, then the coding scheme will find that there is a URL in these tweets. On the other hand if the research intended to create categories that has information about community, it would be coded under community.

One of the first steps then is to create a coding manual. Creating such a schema is important as it allows the coders to interpret the information from data that is communicated at a linguistic level and to group them in their respective categories (Fillmore, 1976). Therefore it is essential to create a referable manual that the coders can use to convert their interpretation into measurable and numerical units to check inter-coder agreement (Zhang & Wildemuth, 2009). However coding is an iterative process and most of the time it requires multiple iteration before finalising the codes (Strauss, 1987). It is only after the coding cycles are completed, that researchers can identify the pattern in the dataset. Furthermore, it is only after the pattern is identified and categorised that high-level abstract constructs and theories can be formed (Morse, 2012).

As grouping related tweets is an important part of extracting information from Twitter, qualitative coding is an important first activity performed by researchers to group the tweets in ways that support the development of a coding schema that can be used to gain understanding about the disaster (Bruns., et al., 2012), as well as form the basis of quantitative analysis (Vieweg, 2012a).

For the first cycle of coding, Vieweg (2012a) used a binary method to divide the tweets as off topic or on topic, with a further division of on topic and related to the disaster and on topic but not related to disaster. This method of binary division is used in this project to quickly eliminate irrelevant tweets before classifying the remainder into their coding groups.

For the second pass of coding, Vieweg (2012a) identified 27 information groups (Table 5) while analysing tweets from three different natural disasters that occurred between 2009 and 2011. Bruns et al. (2012) developed five broad categories with sub categories (Table 6). Both of these approaches contains useful but different methods of observation. Both coding schemas are listed below to gain further understanding about how these schemas can be applied to this research.

	Coding schema by Vieweg (2012a)
Social Environment	Advice - Information space, Animal Management, Caution, Crime, Evacuation, Injury, Offer of Help, Preparation, Recovery, Request for Help, Request for Information, Response - Community, Response - Formal, Response - Personal, Sheltering, Status - Community, Status - Personal
Built Environment	Damage, Status - Infrastructure, Status - Private property, Status - Public property
Hazard / Physical Environment	General Area Information, General Hazard Information, Historical Information, Prediction, Status - Hazard, Weather

Table 5: Coding schema developed by Vieweg (2012a) with regards to natural disaster tweets

	Coding schema by Bruns et al. (2012)
Information	Advice, Situational awareness, Request for Information
Media Sharing	News media, Multimedia,
Help and Fundraising	Help, Fundraising
Direct Experience	Personal narrative, Eye witness report
Discussion and Reaction	Adjunctive discussion, Personal reaction, Thanks, Support, Meta discussion

Table 6: Coding schema developed by Bruns et al. (2012) with regards to natural disaster tweets

As it can be seen, there are a number of similarities between these two coding schema, as well as quite a few differences. While Vieweg (2012a) categorised the codes based on the environment the disaster affected, Bruns et al. (2012) focused on the type of content that was being shared. Selections from both of these coding schema have been used in this project and are further explained in a later section.

Inter-coder agreement The next step of the process, the reading and grouping of tweets based on the defined coding schema, is done by either one or multiple people or computers (Williams, Terras, & Warwick, 2013). The objective of having a human interpreter, or coder, is to convert the subjective judgment of the tweets to measurable units or groups (Krippendorff, 2012).

However, as human coding judgments may vary, in order to improve reliability multiple coders are often used to code the same dataset (Oh, Kwon, & Rao, 2010).

At the end of the process, the coding is compared using established reliability indexes such as Cronbach α or Cohen κ to find out what percentage the coders have agreed on. These reliability indexes can be used to quantify the amount of errors a single source can cause. Therefore, in most cases, when evaluating disaster tweets, multiple coders are employed. And in most cases, there has been consistent agreement on the coding of disaster relatedness (Vieweg, 2012b). For various dataset analysed by Vieweg (2012b), the inter-coder agreement for the majority of the datasets were above 80% kappa value (Cohen κ), and therefore considered good (Manning & Schütze, 1999). Only in one specific case of Haiti, the agreement between the coders were below 67%, thus suggesting it was not a fair agreement.

Even though coding is generally done in a team to reduce the coder-specific error and to improve reliability, when the objective is to gain an understanding of the whole dataset in order to perform future experiments, sole coders are also employed (Burant, Gray, Ndaw, McKinney-Keys, & Allen, 2007; Strauss, 1987). In such situation where solo coding takes place, Saldana (2012) suggests the sole coder consult a mentor or supervisor or even a colleague during the analyses process as a way of validating the findings. According to Ezzy (2013), such practices help to make connections between categories and creates a reflection process that can assist in addressing limitations posed by single person coding. Saldana (2012) argues, even if the result of solo coding is not used for creating a final output, it can be used as an intermediate step as a part of a bigger process.

For the purpose of this project during phase one where the objective was to gain an understanding of the dataset, and in identifying patterns in the smaller dataset before applying to a larger dataset, solo coding took place. The second phase, the coding was conducted using a crowd sourced method which is explained in the next section.

Crowdsourcing A major criticism of manual coding in general is that it takes a long time to perform this task. Since time is an extremely important factor after a natural disaster, researchers have experimented with expanding the number of coders from a handful to thousands (Imran, Elbassuoni, Castillo, Diaz, & Meier, 2013; Norheim-Hagtun & Meier, 2010). With the help of crowdsourcing platforms such as crowd flower and micro mapper, researchers have explored ways they can engage crowds to perform this activity in a large scale (Meier, 2013). As this is a relatively new area of research, there has been limited study on the adaptation of the existing statistical methods with regards to crowdsourcing inter-coder agreement. This is another area that is explored in this dissertation.

Transition to quantitative methods As discussed earlier, most of the natural disaster-based Twitter research uses a mixed methods approach. The first step adopts a qualitative approach where a coding manual is developed and coders are used to code the tweets manually into groups as described earlier. The next step is to create an automated option that can apply these methods of coding to a much larger dataset. From the previous examples, Vieweg (2012a) used a coding scheme together with natural language processing where verbs were used as the basis to determine the communication pattern in the dataset, and then grouped them into a specific category as developed in the qualitative step. Similarly, in addition to grouping tweets based on their content, Bruns et al. (2012) also counted various embedded objects in the tweet such as URL, RT, @replies, use of # (hashtag), time and date to identify which coding group that particular tweet may fall into, or who the message was sent to. The next section describes how other researchers have used quantitative approaches with Twitter data and which of those were adopted in this dissertation.

3.3.2 Quantitative analysis methods

Quantitative methods refer to systematic empirical investigation with the help of computational, statistical and mathematical approaches. As Twitter generates a large amount of data in a short period of time after natural disaster, research often uses quantitative methods on its own or extends the qualitative method to identify patterns and extract important information from Twitter. Compared to qualitative methods, often both the content of tweets and the metadata gets used when quantitative methods are employed. This may be to test if a breaking event such as natural disaster has occurred (Yin, et al., 2012), or determine what are the specific situational awareness tweets that are appearing in Twitter (Corvey, Vieweg, Rood, & Palmer, 2010; Döhling & Leser, 2011).

A number of Twitter components are suitable for quantitative analysis. Among them the most prominent is the hashtag. Although hashtags are usually not counted to understand the contents of the tweet, they are useful for identifying the size of the sample, or to determine if the data being collected is of significance (Potts, Seitzinger, Jones, & Harrison, 2011). For example, it is expected that after a natural disaster a dominant hashtag would generate a substantial amount of tweets (Hendrickson, 2012b). If the hashtag does not generate substantial amount of data it is possible that either the hashtag is not dominant or the event is not significant. Therefore hashtags can act as the first data validation point.

Keywords on the other hand are widely used to identify how often a specific event occurs . By identifying the frequency of the keywords it is possible to gauge what type of disaster has happened or what type of information people are looking for or sharing. However counting keywords alone is often problematic, as keywords themselves do not describe the context of the tweet. This has resulted in extensive research that uses various methods to identify the context of the keywords. In the following sections several of these methods are explained in detail.

Other basic building blocks of Twitter can also generate quantitative data. @reply or @mention are useful for identifying prolific users, and to create network graphs of interactions or indications of impact (Bruns., et al., 2012). Counts of retweets suggest visibility of tweets or the user as they can amplify conversation as it allows users to broadcast a specific message to their own followers. Although for the purpose of emergency services retweets are often considered as unimportant (Mendoza, Poblete, & Castillo, 2010; Thomson et al., 2012), they can be useful in certain situations such as in the case of the Christchurch earthquake where a tweet about the CTV building was retweeted a number of times before the building collapse became prominent (Paul & Bruns, 2013). Therefore the viability of using retweet in determining importance is considered in this dissertation.

Embedded objects such as URLs, images and video also contains relevant information. For example, a highly shared URL may contain information about the disaster warning or information from media. Although for the purpose emergency services, URL information may have limited use, research has used counts of URLs to identify message dissemination in Twitter. Images and videos are one of the most useful features in assessing the amount of damage caused by the disaster (Muralidharan, Rasmussen, Patterson, & Shin, 2011). Unfortunately the number of fake images spread through Twitter is also high. Moreover, fake images tend to get more visibility with retweets due to their quirkiness (Gupta, et al., 2013). However, images remain an important entity to identify important information during disaster.

Apart from the contents of the tweet, metadata can be counted and used to identify patterns as well. For example, tweet creation time and date metadata is often used to create temporal analysis or to identify a section for further analysis. By counting when the particular message appeared in the tweet, Cataldi, Di Caro and Schifanella (2010) identified the temporality of the tweet and if it is still relevant.

The geo location feature of Twitter is also useful metadata for emergency services. Although the number of users who share their geographical location with Twitter is often below 2% (Hossmann, et al., 2011), it is regardless important metadata to consider. In cases where geo location data is not available, related metadata such as user's time zones have also been used to identify the potential location of the user (Hale, et al., 2012). Since location metadata contains useful information, researchers have converting time zone to location and extracted named entities from the tweet itself (Jung, 2012; Li, et al., 2012; Liu, et al., 2013). These additional metadata are also being used during quantitative analyses to identify various patterns in Twitter.

Overall, there are many features that are used by Twitter researchers to analyse tweets quantitatively. The following sub-section describes various methods researchers have used to analyse the above mentioned tweet content data as well as metadata in order to find relevant information from Twitter. This is then followed by a justification for applying some of these methods in this project.

Word Frequency In Twitter research that uses computational methods, detecting whether a natural disaster has happened falls under the category of event or topic detection. Both of these terms are often used interchangeably because any breaking event creates topics (although not all topics become a breaking event). The usual approach is to count the frequency of given terms over a period of time and if the frequency is higher than the usual rate, it can be considered as a potential breaking event (Petrovic et al., 2013). Sakaki et al. (2010) have utilised this method to detect earthquakes in Japan and alert the community that a potential earthquake may occur.

As quantitative methods focus on counting and measuring, such frequency counting is one of the most popular analysis methods used in quantitative studies. In terms of topic detection, the most visible topic detection is the trending topic, which displays currently popular keywords and hashtags in the specific geographical area and is displayed by Twitter on their homepage using proprietary algorithm (Lee et al., 2011).). Trending topics were introduced by Twitter in 2008 and has been widely used ever since (Abrahamson, 2012). Due to the sudden burst of tweets, disaster keywords often become trending topics in Twitter, which prompted some researchers to use it to identify disaster relevant tweets (Lee, Yang, Chien, & Wen, 2011).

However, according to Lin and Mishne (2012) trending topics can depend more on the velocity of tweeting than the volume, as interest changes quickly in Twitter. Furthermore, a topic might feel popular but may not generate enough volume of mentions compared to other topics which might not seem popular in order to be listed as trending topic (Twitter, 2010). Furthermore, sometimes even if a topic generates huge volume of interest, but is outpaced by other topics in terms of velocity of mentions, the initial topic might get delisted by the newer entries.

Overall, although trending topics may be useful to identify if a disaster in progress, the trending topic can also contain a large number of frequently appearing tweets, making it difficult for emergency services to isolate relevant information. In addition, even though trending topics are a useful indicator of highly popular tweets, it is less useful for emergency services as it usually takes a few hours for a topic to become trending (Mendoza, et al., 2010). Therefore, even though it suggests the topics are related to breaking event, as trending topics can be slow to appear in the list, this measure has not been used in this research.

Detecting a bursty topic on the other hand is a more useful method. This refers to a sudden spike in the dataset. Various researchers have used the bursty topic to detect potential hazardous events through Twitter (Yin, et al., 2012; Z. Wei, 2011). The common way to use bursty topic detection is to assign a list of keywords, which can include part of a keyword, to identify if there is a sudden increase of the use of that word. For example, Hendrickson (2012a) used the word earthquake to detect more than 800 thousand tweets after the Mexico earthquake. Thus usage of the bursty topic is a commonly used method detect sudden event.

Counting the frequency of other components has also been used in Twitter research. Bruns et al. (2012) used number of replies received by a user to identify impact, and a count of retweets to determine visibility of a tweet. In order to compare communication patterns across a dataset, Bruns and Stieglitz (2012) used counts of other entities, such as URLs, to identify the difference between types of events. Lin and Mishne (2012) used a combination of keyword count with the speed that tweets appear, to identify if an event has recently occurred.

Word frequency counting has also been used to identify an area that has a power outage, and to provide road and traffic situation information using Twitter after the Japan tsunami (Huang, Liu, Du, & Cheng, 2014; Utani, Mizumoto, & Okumura, 2011). Usahidi mapped the count of location names to a mapping system and were able to showing visually which area had more reports of damage, this providing a quick visual indication of the status of damage. Robinson et al. (2013) also mapped tweet counts that contained the word earthquake to create a quick look of affected areas in the New Zealand earthquake.

The limitation of using word frequency searching in an emergency is that once a disaster already happened, the next course of action for emergency services is to help people, and therefore identifying a breaking event is less useful. However, as it can be seen from prior research that tweets containing disaster related information in a disaster that continues for a long time (e.g. flood) or comes with a few days of warning (e.g. cyclone), have an up-down trend (Bruns, et al., 2012). The up-down trend happens because people don't tweet when they are asleep and therefore total amount of tweets reduces at night and then rises again during day. However, if there is a sudden change in event, there is a sudden spike in tweeting activity regardless of the time. This method can therefore be used after the first major event to detect if a certain area has been affected by a second wave of disaster, or to identify if the severity of damage has increased in a certain location. Although there has been extensive research on methods to improve the technique of bursty topic searching, research has generally used universally known keywords to identify the burst (Platt, Hood, & Citrin, 2011; Aggarwal, 2011; Becker, Naaman & Gravano, 2011). There has however been limited research on which keywords actually appear in Twitter that signal the type of information needed by emergency services. Therefore this research looks at identifying a list of keywords and proposing a framework to identify such words.

There is an additional challenge that is associated with the use of the frequency of entities. Counting only single entities such as keywords, replies, retweets or URLs may not provide enough information to identify if the tweets share the same context. Therefore it is necessary to find a way to group individual tweets in a cluster or classify them individually using various methods. Some of these classification and clustering methods are addressed in this later sections of this chapter.

Natural language processing As it can be seen from the previous sections, although identifying patterns can be useful way to find breaking events and topics, for the purpose of emergency services, finding information from individuals tweets is more desirable (Goyet & Morinière, 2006; Lorch, 2005; Telford, Cosgrave, & Houghton, 2006). With the increasing use of social media in natural disasters, the expectation from people that they will have their message heard by emergency services, it is becoming even more important to identify and categorise individual tweets according to whether someone is asking for help or providing information about the location (Reynolds & Seeger, 2012). Thus another widely used method to analyse disaster related tweets is natural language processing (Corvey, Vieweg, Rood, & Palmer, 2010). There has been extensive amount of research in this area that deals with various forms of natural language processing (Valero, Gómez, & Pineda, 2009; Verma, et al., 2011; Vieweg, Hughes, Starbird, & Palen, 2010; Vlachos, 2011). This includes dictionary lookup, word sense disambiguation, part-of-speech tagging, counting frequency of unigram, bigram or a combination of these methods.

Dictionary of keywords Dictionary lookup is generally the first approach when using natural language processing to classify Twitter data (Han, Cook, & Baldwin, 2013). The process of dictionary lookup is done by breaking each tweet into words or tokens, known as tokenization, and to then compare that with words in the dictionary. The common problem with Twitter is that a significant amount of tweets do not comply with traditional spelling. For example it is normal to use the word b4 to represent before. To address this issue Han et al. (2013) suggested normalising texts to match regular vocabulary in the dictionary.

Similarly, it is also common to perform other removal processes to reduce the number of counter-checking of word and their variants with the dictionary. This process often involves eliminating non-representative words such as conjunctions and prepositions, as well as short function words, such as ‘the’, ‘is’ and ‘which’, in order to leave the bare essential words in a single tweet. This process is then followed by a further reduction of words into their original form through a process called ‘stemming’ (Imran, et al., 2013), which converts plurals, adverbs, adjectives into the basic word.

However, there are several limitations when applying these research methods in a disaster situation. A notable limitation is the lack of a relevant referable word list (also known as a dictionary) and of a framework to create such a list that contains the words that need to be counted. For example, in a flood the commonly used words would be water, rising, filling but in earthquake it would be shake or broken (Yin, et al., 2012). The unavailability of such lists makes it difficult to identify which words are more important than others. Furthermore, such a list would also need to be updatable, as people learn new words in a disaster situation and use that to refer to the disaster. For example, in the Christchurch earthquake, people started to use a term called “liquefaction” shortly after earthquake to refer to the soil becoming liquid and coming out of the ground (Reyners, 2011). Since this is not a commonly used term, this would not be in the word search dictionary, demonstrating that such a dictionary needs to be updatable. A framework that can identify the words used and add new words would be useful to isolate potential disaster related tweets from those that are not related.

One could argue then that as the topics of conversation continuously change in Twitter, having a static dictionary is pointless. However, as it has been seen from various research (Mandel et al., 2012), a list of keywords that can be used as a starting point would be a useful addition to the body of literature. Therefore one of the tasks of this project is to identify a mechanism to create such dictionary from disaster tweets.

Co-occurence of keywords One of the biggest issues of identifying individual keywords using a dictionary lookup method is word sense disambiguation (Banerjee & Pedersen, 2002). For example, by looking at a single word ‘foundation’, it is difficult to determine if it belongs to a foundation of a building that is flooded or it is a foundation that has donated money for flood victims. Owoputi, O’Connor, Dyer, Gimpel, Schneider, & Smith (2012) suggested grouping phrases that co-occur even though based on a dictionary they are unlikely to be together. Through this process it is possible to identify a theme based on co-occurring words. For example, by comparing the word group ‘water’ and ‘food’ with ‘flood’ and ‘water’, it is possible to identify themes, such that the first group is potentially describing a need, whereas the second group is describing the situation. As this is a useful theme identification method, it is adopted in this dissertation.

N-gram Before going further it is necessary to address other commonly used methods for natural language processing in Twitter research. One of the most notable methods is n-gram, which is a contiguous sequence of items (where n refers to the number of items) in a sequence of text (Dunning, 1994). The question of how many words should be grouped together was addressed by various n-gram methods (Verma, et al., 2011). Bermingham and Smeaton (2010) have found the unigram method to be better than the bigram method in finding sentiments from tweets. However, Verma et al. (2011) found that bigrams perform better than unigrams or trigrams when analysing a Twitter dataset. Due to the similarity between a bigram of words and the co-occurence of words, the n-gram method was not tested in this research.

Sequential pattern mining A more advanced extension of n-gram is sequential pattern mining (Zhong, Li, & Wu, 2012). Sequential pattern mining finds statistically relevant patterns between datasets provided that they are presented in a sequence. Lau et al. (2012) suggested using sequential pattern mining to identify topics, as the order the information appears is crucial in understanding the context of the keyword. Although this is a useful method of identifying topics from tweets, it is more relevant to news organisations than for emergency services. This is because, pattern mining is useful for identifying topics from a set of unknown tweets, but in natural disaster, the information that is required is often known and the question is instead, if the tweet contains that information. Therefore this method was not used in this project.

Parts of speech In addition to the sequence of words in sentences, another area that has been researched in the disaster related Twitter research is parts of speech. The part of speech is a useful method to identify which lexical category the particular word is in. Although traditionally this approach considers eight different lexical categories (noun, pronoun, adjective, verb, adverb, preposition, conjunction, interjection), Chris and Schneider (2012) introduced new categories that can identify short forms such as idk (I don't know) and imho (in my humble opinion) to gain more understanding about tweet content.

Named entity extraction Identifying the location of disasters is a critical factor for emergency services (Davis Jr., et al., 2011). As mentioned earlier, extracting this information from Twitter can be problematic due to concerns with privacy and users not utilising their GPS (Hale, et al., 2012; Harvey, 2014). This is where named entity extraction can be useful as named entity contains the name of the location, person, organisation, time, being able to identify location, person or organisation from tweets can assist emergency services to identify tweets that are disaster relevant. Therefore named entity extraction (Klein, et al., 2003; Ritter, et al., 2011; Tjong Kim Sang & De Meulder, 2003) can be useful for emergency services in identifying location from tweets. The application of this approach is discussed in details when it is used in the chapter five.

Classification In its simplest form, tweet classification is meant to identify if a tweet is relevant or not relevant for emergency services (Banerjee et al., 2012; Sriram, Fuhry, Demir, Ferhatosmanoglu, & Demirbas, 2010; Vitale, Ferragina, & Scaiella, 2012). However, as Twitter generates large volumes of data after a natural disaster, classifying only according to useful and not useful is not enough. For the purpose of emergency services it also need to be identified if the tweet is asking for help, providing information about the location or seeking medical advice (Below, Wirtz, & Guha-Sapir, 2009). One of the advantageous of using a classification algorithm is it can predict categories with the help of classifiers.

The general approach to classification usually consists of two step process where the first step is learning and the second is classification. This process is similar to qualitative coding, where a coding schema is generated first and then coders manually read tweets and group them into categories. Classification algorithms achieve similar results by first learning which categories exist from the data and then assigning these categories automatically in a larger dataset. It is common to apply various classification algorithms such as rule based classification, support vector machine (SVM), bag-of-words, term frequency - inverse document frequency (TF-IDF), Naive Bayes, maximum entropy (MaxEnt), decision tree or random forest (RF) to automatically categorise Twitter data (Castillo, Mendoza, & Poblete, 2011; Roy Chowdhury, Imran, Asghar, Amer-Yahia, & Castillo, 2013). Sakaki, et al., 2010; Sakaki, Toriumi, & Matsuo, 2011) These approaches have been used to identify an earthquake as it happened, with SVM being used to group tweets based on their region and therefore suggest which is the next area that might be affected (Sakaki, et al., 2010; Sakaki, Toriumi, & Matsuo, 2011). Yin et al. (2012) used the bag-of-words and TF-IDF method of breaking tweets to tokens and then assigning scores to the tokens, in order to rank the tweets in disaster times.

However, these techniques are more useful for identifying breaking events or news topics (Osborne, et.al, 2012; Petrovic, et al., 2013) rather than individual tweets. In addition, methods such as TF-IDF is problematic for Twitter as tweets are not long enough to have an effective IDF score; and since rarely the same word appears twice in the tweet, there is no difference between document frequency (DF) and term frequency (TF) (Sriram, et al., 2010). Therefore, even though Yin et al. (2012) have used TF-IDF scores to assign weights to tweets, the approach is not universally accepted (Bontcheva & Rout, 2014).

In addition, Imran et al. (2014) argues that pre training classifiers do not work from one disaster to another. Therefore the suggestion is to utilise crowdsourcing as a filtering mechanism. Unfortunately not all emergency services have the means and ability to utilise crowd source platforms immediately after a disaster strikes. It might be better to identify if the information that emergency services require can be identified using simple rule-based classification that utilises a dictionary lookup method. Therefore this project attempts to identify if tweets contain information that emergency services need and if it is possible to create a dictionary that can be used by other researchers as a starting point.

Clustering   Clustering by definition groups a set of objects to find whether there is a relationship between the objects. It is essential to address clustering as clustering is a popular research method for Twitter. The objective for using clustering is to identify if there is a relationship between the tweets in order to cluster them into a category. A number of researchers have used clustering to group messages in their related category using known algorithms such as k-means (e.g., Sasongko & Tjondronegoro, 2010; Silva et al., 2013; Thaiprayoon, et al., 2012). As actionable information is a top priority for emergency services clustering can extend the grouped information in their own cluster to create a quick visual representation (Rangrej, Kulkarni, & Tendulkar, 2011). For example, emergency services may want to know which area needs more food and water, compared to only identifying the fact that people are looking for food and water, and clustering that with the name of a location may suggest that one area is more affected than another.

Clustering analyses partitions the objects in various subsets. It can be clustering of words, co-occurred words, URL, geo location, or other entities that are extracted through natural language processing or classification methods. Clustering methods usually fall under partitioning, hierarchical, density based or grid based methods.

The k-means method is one of the most popular partitioning methods used in clustering tweets (Karandikar, 2010; Silva, et al., 2013). However the problem of k-means, is in order to identify the clusters, the number of clusters needs to be pre-identified (Lau, et al., 2012, Yin, Lampert, Cameron, Robinson & Power, 2012). Yin et al. (2012) further argues that since the Twitter dataset is often unpredictable, it is difficult to use clustering algorithms in Twitter with a priori knowledge of how many clusters are needed. Karandikar (2010) have used the manual scanning of topics generated by initial clustering algorithms to suggest how many clusters to specify, and then used that for further detection. Such approach at the time of disaster is difficult as in the initial stages there may not be enough variety in the messages to identify the number of potential clusters.

Other information retrieval approach   In addition to the methods already discussed, there are other approaches of topic detection that uses external metadata from other online resources. The most notable of them is use of wordnet and Wikipedia (Sriram, et al., 2010). Wordnet is one of the largest English lexical databases that groups words based on their synonyms (Miller, 1995). It has been used in numerous information retrieval projects (Shvaiko & Euzenat, 2013; Zhang, Islam, & Lu, 2012). However, the issue with wordnet is that even though it contains a large number of paraphrases, synonyms and other lexical features, words in Twitter often do not follow lexical patterns. Instead identifying topics based on wikipedia instead of wordnet has been recommended (Hu, Zhang, Lu, Park, & Zhou, 2009; Osborne, et al., 2012). For the purpose of this research, external metadata from wikipedia was therefore looked at.

3.3.3 Mixed method approach

As it can be seen from the discussions so far, both qualitative and quantitative methods are useful for Twitter researchers. In some cases, independent researchers working with Twitter datasets from same event using qualitative and quantitative method have produced similar outputs, as shown by the examples below.

For example, Bunce et al. (2012) wanted to identify people's information experience during the 2011 Queensland flood following the blog post of Axel Bruns regarding the emergence of social media networks. Therefore using semistructured interviews they asked people about their information experience during the Queensland flood. By taking a deep data approach, they identified four categories of information experience: monitoring information, community and communication, affirmation, and awareness.

These findings were similar; although not identical to those reported by Bruns et al. (2012) in their CCI floods report. The CCI findings were based on a surface data approach, where they collected and evaluated large datasets by finding the patterns in the data instead of going through individual tweets. Based on that analysis for the same event they identified the categories of information, media sharing, help and fundraising, direct experience, reaction and discussion. The interesting part of both of these approaches is that whilst both focusing on social media in the same event, they used different methods to uncover similar categories that were potentially relevant for emergency services.

However, instead of relying only on qualitative or quantitative method, mixed method has been growing in popularity among Twitter researchers because it allows researchers to gain a deeper understanding about a situation while being able to analyse a large of dataset at the same time (Bruns & Liang, 2012). Although rigorous research may produce similar results through quantitative and qualitative studies, combining both of these methods allow Twitter researchers to draw from the strength of both research methods. In such mixed methods studies in Twitter, an initial study is conducted using qualitative methods to identify which features potentially makes a tweet relevant for emergency services from a human perspective before testing them with automated methods. An example of this approach can be seen from Huang, Thornton & Efthimiadis (2010) where the researchers started with interpretive analysis to understand conversational tagging of Twitter and Digg dataset before using statistical analysis to find the difference in tagging pattern between both of their dataset.

This whole approach of going back and forward between qualitative and quantitative approach is used in this research and explained in details in the next section, the research design.

3.4 Research Design

The primary objective of this research is to identify and extract important information from social network streams during times of disaster. Therefore the research firstly looked at identifying what is important, and then how can it be automatically identified in social media during a natural disaster.

The research design used a mixed method approach that combined qualitative and quantitative analysis methods. The qualitative approach included performing content analysis on tweets by evaluating them manually - at first using a sole coder and later via a crowd sourcing platform. The quantitative approach included using an off the shelf software package for a smaller dataset in the first round of analysis and later developing a bespoke set of tools and analysing a larger dataset to identify important information. Figure 13 shows the process of this research, where the steps flows from one stage to another. Findings from a smaller dataset are tested against a larger dataset and then those modified findings are used to change the model that is tested on next dataset till the final outcome is reached.

The reason for using two groups of datasets was the diversity that these two groups possessed. Although the collection process remained almost the same (and is explained in next section), the Queensland flood dataset, which was collected in early 2011, contains data from single hashtag during a time when Twitter was not widely used. Comparatively, the Yolanda dataset, which was collected in late 2013 using multiple hashtags from a different location, was done so in a time where the usage of Twitter had grown significantly. Therefore analysing these two groups of datasets can provide valuable insights in the way users communicate in Twitter and how this communication might have shifted over time, so to identify what is important for emergency services. In the following sections both the single and multiple hashtag datasets are discussed, including the reasons why they were selected and how the data was collected.

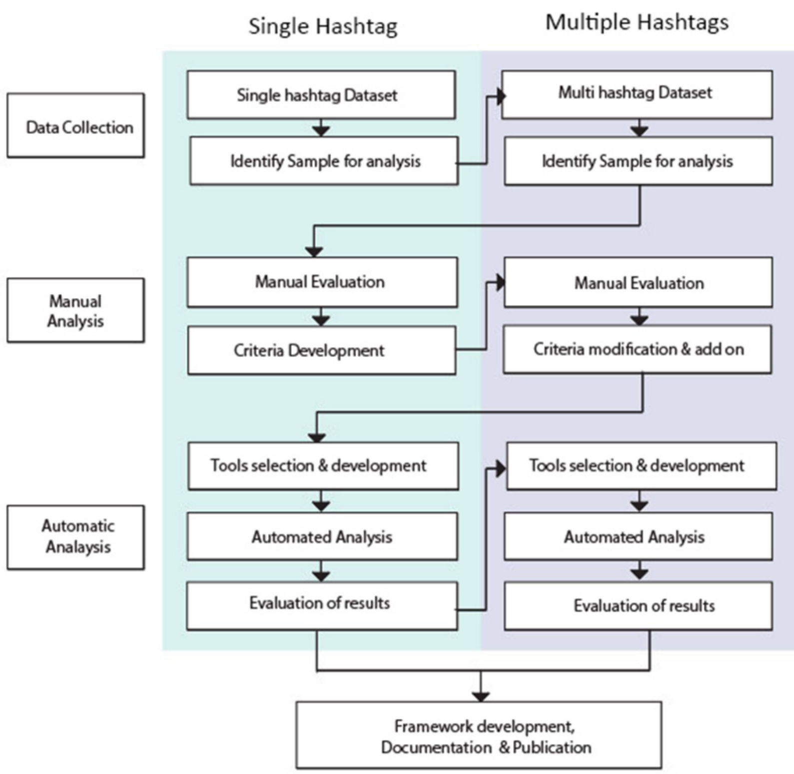


Figure 13: Research Design Flowchart

3.4.1 Data collection and sample size

Both datasets, the QLDfloods and the Yolanda dataset were collected using Twitter streaming API. As streaming API only goes forward, this dataset does not include any tweets that had the hashtags or keywords before it was recorded in the collection system. This section describes the sample size as well as the collection procedure.

Collection Tool The QLDfloods dataset was collected using yourTwapperkeeper, as it was the most popular open source collection tool in 2011. Generally the criteria for choosing a collection tools involved decisions such as how easy it is to setup, the cost and resources need to run the tool, and most importantly, what data it can collect. Based on the available tools at that moment, yourTwapperkeeper (yTk) was the best solution as it was an open source version with relatively easy setup options and it could capture from streaming API. It was also already in use by various other researchers such as Yang and Kavanaugh (2010). Therefore for the collection of the QLDflood dataset yTk was used.

The Yolanda dataset was collected using the collector part of the AIDR tool (Imran, et al., 2014). Developed at QCRI, the collector tool works in the same way as yTk; once a user authorises the tool with their Twitter authentication page (details in the Appendix B), users can include hashtag or keywords and it starts collecting any tweet that includes that hashtag or keyword.

Collecting data and size of the dataset Using hashtag based sampling, a total of 49,748 tweets were collected using the #qldfloods hashtag from 5th January 2011 to 9th February 2011. The tracking of the flood on Twitter began after the start of the flood in the north of Queensland in December 2010. When flood hit Brisbane and the Gold Coast in January 2011, the hashtags were already being tracked, which ensured the method captured tweets from the early stages of the event.

About 230,000 tweets were collected from Twitter streaming API using related hashtags and keywords that included; #yolandaph, #hurricane, #haiyan, #typhoon, #Philippines, #yolanda, as well the keywords without hashtag; yolandaph, hurricane, haiyan, typhoon, and Philippines. Other related words, disaster, wind and the nearby areas of Vietnam and Korea that fell in the typhoon path were also included. After category 5 typhoon Yolanda (also known as Typhoon haiyan) hit the Philippines at 3am on the 8th November, 2013 (Philippines time), people from Philippines and the rest of the world began to flock to Twitter. This was one of the most disastrous typhoons with the strongest wind speed ever recorded in history. As information gathered during first 24 hours are the most crucial (Queensland Government, 2012a) QCRI used tweets collected in the first 24 hours for crowdsourcing purposes, and this research analyses that data. This dataset was made available to the researcher for use in this PhD research through a personal connection with Dr. Patrick Meier.

From the 230,000 tweets collected, standard classification techniques described by Imran et al. (2013) and Chowdhury et al. (2013) were used by QCRI to automatically filter the tweets for relevancy and uniqueness. This reduced the number of tweets to 26,664. These tweets were then used by Tweetclickers, the crowdsourcing micro mapping tool for categorisation. The process of categorisation through crowdsourcing is described in next chapter.

Limitation The primary limitation of this method of collecting data is, as the keyword and the hashtags were added manually, it is possible to miss hashtags or keywords that might have used at the beginning of the disaster prior to entering the hashtags in the tracking system. As mentioned earlier, streaming API does not allow the capturing of historical data and search API limits the number of data stored, although it does allow access to older tweets.

Taken together the phases outlined in the research design represent a mixed methods model that capitalises on the potential of qualitative and quantitative approaches. Each phase is designed to generate the best possible features from tweets that can be used by emergency services to identify disaster related information. The question remains is, how the results of this research can be evaluated which is discussed in the next section.

3.5 Evaluation of Outputs

Validating a predictive model is necessary to ensure the outcome of the model is satisfactory (Bollen, Mao, & Zeng, 2011). Since this research analyses a tweet and suggests if the tweet is likely to be relevant for emergency services, the output of the algorithm needs to be validated to ensure it produces an accurate result. Although this research does not intend to create a solution that will automatically classify an incoming tweet without any human intervention, the algorithm aims to reduce the number of tweets that emergency services need to evaluate manually.

Therefore, the outcome of the algorithm needs to be evaluated to ensure it has a satisfactory performance. In computer science there are several methods of evaluating such models and this section discusses various validation methods used by Twitter researchers to determine which of these methods is applicable for this research.

3.5.1 Cross validation

One of the most common validation methods used by Twitter researchers to predicting if a tweet or dataset will answer their research question is the k-fold cross validation method. In a k-fold cross validation, a dataset is divided equally in k number where one of the subset of data is used for validation and rest (k-1) used for training. Verma et al. (2011) used a 10-fold cross validation to find which features were better at finding disaster related tweets. Davidov, Tsur and Rappoport (2010) similarly used a 10-fold cross validation to identify sentiments.

However, the method of using cross validation is most useful when both the training and validation set are time independent (Amari, Murata, Muller, Finke, & Yang, 1997). Since the contents of the tweet in the early stage of a disaster are likely to be time dependent, cross validation methods may successfully identify disaster relevant tweets for the same dataset but may not work for new data from the same event. Therefore cross validation was not used as the validation method.

3.5.2 Outperforming a random baseline

An alternative evaluation method is to test if the outcome outperforms a random baseline. Although this method is similar to cross validation as it uses portion of the same dataset, the difference with cross validation is that instead of comparing with an equally divided portion of the dataset, the approach compares the result with a random chance (Ramage, Dumais, & Liebling, 2010). The performance of an algorithm against a random baseline has been used in much computer science research (e.g., Baldi, Brunak, Chauvin, Andersen, & Nielsen, 2000; Pang, Lee, & Vaithyanathan, 2002; Speriosu, Sudan, Upadhyay, & Baldridge, 2011). Petrovic, Osborne and Lavrenko (2011) found that when it involved the prediction of relevance at an individual tweet level, evaluating against random chances often produces acceptable classification solutions. This method of evaluation was used in this project, and thus the remainder of this section provides an overview of that process.

Identifying a random baseline The first step in this process is to identify a random baseline. In order to that, the probability that a given tweet in question is related to disaster (and emergency services) is calculated. The formula used to calculate the basic probability is below (DeGroot, Schervish, Fang, Lu, & Li, 1986).

$$\textbf{P (tweet is relevant for emergency services) =} \ \frac{disasterTweets}{totalTweets}$$

The second step is to identify the probability that a tweet is related to the disaster and relevant for emergency services given that it includes the feature previously identified. This is done using a conditional probability formula.

P(tweet is relevant for emergency services | feature) = the probability of a tweet is relevant to emergency serivces GIVEN the tweet contains that feature.

If the result of the conditional probability is worse than random, it can be concluded that for that tweet that specific feature does not outperform the random chance, and is therefore not a good filtering feature.

Combining features However, as the discussions in this chapter and the literature review suggest, a single feature is unlikely to be able to be the point of difference that identifies if a tweet is relevant for emergency services. A combination of multiple features however can potentially identify if a tweet is relevant for emergency services. In order to do that researchers usually use a ranking algorithm that calculates a score for each tweet before combining them to find a final score

(Huang, et al., 2014; Lau, et al., 2011). If the score is less than the cut off score, it is then classified as either relevant for emergency services or not relevant. Linear regression algorithms are usually used in this case and is discussed next.

Linear regression In recent years there has been a growing number of research that uses Simple Linear Regression (Ginsberg et al., 2008) and Multiple Linear Regression models to analyse posts in social network websites or search engine queries to predict crisis related situations such as disease outbreak (Culotta, 2010). Due to the similarity of information diffusion in crisis related situations both of the linear regression models stand are suitable to use in this research.

However, Culotta (2010) suggested that when there are multiple determinants of a measurement outcome, the Multiple Linear Regression model outperforms Simple Linear Regression. As this research uses multiple independent variables (such as existence of image, location, keywords), Multiple Linear Regression has been chosen as the model to calculate the score of the tweets. The formula is:

$$y_i = \beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + \ldots + \beta_p X_{ip} + \varepsilon_i$$

Where y_i is the total score from a tweet. X_{i1} To X_{ip} are the features that have been identified in the qualitative method as the marker of relevance, and β_j (β_1 To β_p) are the coefficients. In the equation β_0 is the 'intercept' which is the expected mean value of y_i when all $X = 0$. For the purpose of this thesis, β_0 is 0 as existence of no variables should result in no value for the score.

Identifying regression coefficients From the previous discussions, it can be seen that the features (X_{i1} To X_{ip}) are the features that were identified through the qualitative approach. In order to determine the coefficients to use β_j (β_1 To β_p), Taylor (1990) suggests that the most common way is to find the difference between that feature and a random feature. For example, if randomly there is a

10% chance that a tweet is related to the disaster and including one feature increases the chance to 20%, then the regression coefficient will be 2.

Sample calculation To illustrate how this formula may work to identify a score of a tweet, a sample scenario can be constructed. If three features were identified as of importance,

1. If the tweet has none of these features, the score will be equal to 0. $y_i = 0$

2. If the tweet has only one feature, and the coefficient for that feature is 3, then $y_i = 3$.

3. If the tweet has two features where one has coefficient of 3 and one is 1.5, then $y_i = 4.5$

Based on this example, if the cut off score is set to 4, only one of the tweet (no 3 in the list above) will be classified as relevant for emergency services while other two will be classified as not relevant.

In conclusion, it is necessary to evaluate methods to ensure they perform the task accurately. However due to various factors not all methods used for evaluation in computer science are appropriate for every research. The method of creating a score to evaluate the output described here is not meant to be the final output, but the objective is to reduce the number of tweets that require further qualitative evaluation. This evaluation using multiple linear regression is discussed in further detail in the discussion chapter.

3.6 Summary

To date various methods have been developed and introduced to analyse Twitter data. The mixed methods research study described in this chapter was chosen as it uses both qualitative and quantitative methods. Among various data types that can be gathered, tweet data was chosen for this research, the content of which is then evaluated through qualitative methods to identify which features makes a tweet potentially relevant for emergency services. The findings are then used to automatically identify relevant tweets using quantitative methods. Once the results are achieved they are evaluated against random baseline to ensure they identify relevant tweets.

In the next chapter, chapter 4, the findings from the qualitative study are presented. This is followed by the quantitative study which is described in chapter 5. The evaluation process is discussed in chapter 6.

Chapter 4: Manual Analysis

The outcomes presented in this chapter address the central research question of this thesis about **finding relevant information for emergency services from social media** during and after natural disaster. As the question of relevance is qualitative in nature, this phase uses a qualitative methodology to address this question. Also termed Phase One, this chapter describes the qualitative methods and processes of analysis, along with the findings. This phase used an iterative process that involved manual reading of tweets using a single coder and crowdcoding. This was done in order to find features of tweets that can identify if a tweet is relevant for emergency services. Based on the findings this chapter proposed a working hypothesis to answer the research the question on relevance.

The studies in this chapter were conducted in two parts. The first involved creating a refined coding schema based on literature. This was followed by manual reading, explorative categorising, evaluation and criteria development from the #qldfloods dataset sample. The second part repeated the same process with a sample from a crowd filtered and crowd categorised dataset, Yolanda (Figure 14). Both of these datasets were gathered during a natural disaster, but they occurred in different times and locations. The sampling is addressed in the next section.

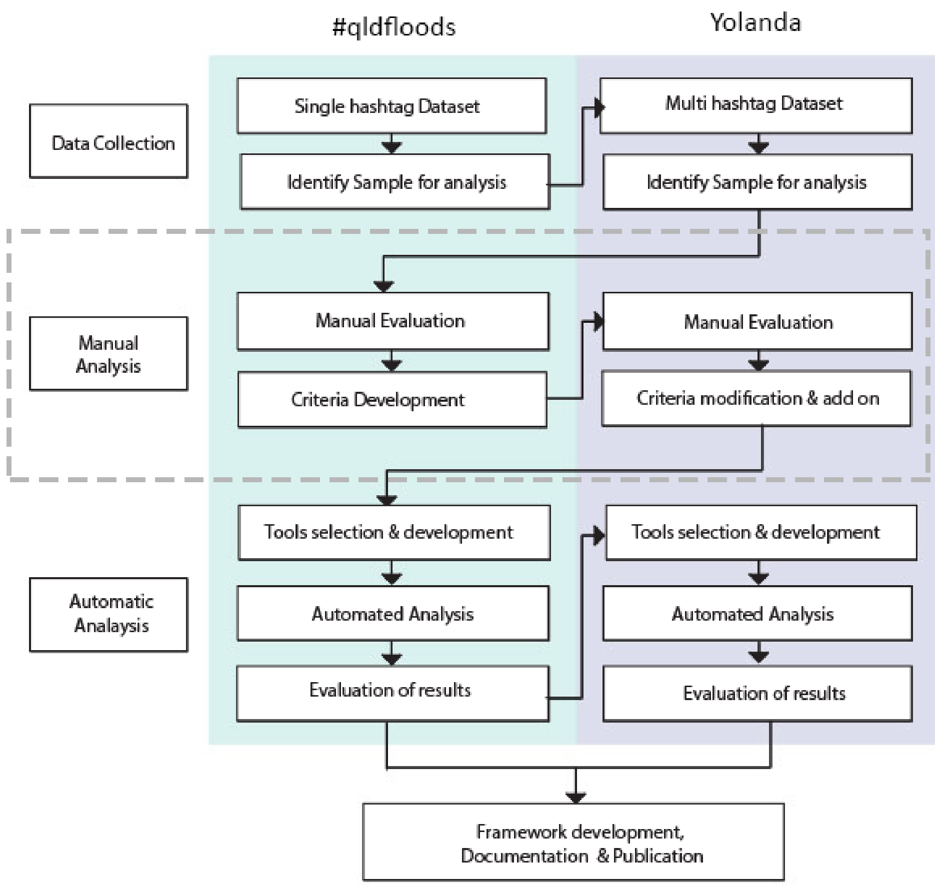


Figure 14: Research design flowchart – manual analysis (phase one)

At the end of both parts of this phase, a working hypothesis was created for the quantitative analysis termed Phase Two.

4.1 Sampling for Manual Analysis

This section explains the process of selecting the sample from the dataset. As this is a qualitative phase, the sample size needed to be reduced from the entire dataset in order for it to be readable by a human coder. For phase one part one, total of

1,320 tweets were evaluated from the #qldfloods dataset. For phase one part two, 293 tweets were evaluated from Yolanda dataset.

4.1.1 Sampling for phase one part one

Total of **1320 tweets from #qldfloods dataset** were selected for the part one analysis. The size of the initial sample gathered for #qldfloods was 49,748 tweets. Since this is a large amount for manual reading, it was reduced to the smaller size. Using the stratified sampling method suggested by Bakshy et al. (2011), the approach utilised was to identify the time that most tweets were captured. This is because the high number of tweeting activity may represent a potential breaking event or an important change in the situation.

The first step was to filter out tweets that used the word "RT". This is because retweets that were captured in the dataset were essentially duplicates of what was already in the dataset. This step brought down the number to 17,983. As this is also a large number, the next step was find out which days had the most number of tweets. In order to do that, the data was put into a pivot table and sorted based on the count of tweet per day. As it can be seen from Figure 15 the day with the highest level of tweeting was the 12th of January 2011. A total of 4,054 tweets were archived using the #qldfloods hashtag on those two days.

A second round of filtering was performed to select tweets from the hours that had the highest number of tweets. The six hours from 9 a.m. to 2 p.m. were selected as they had the most number of tweets on the 12th of January 2011, as well as showing an upward trend (Figure 16).

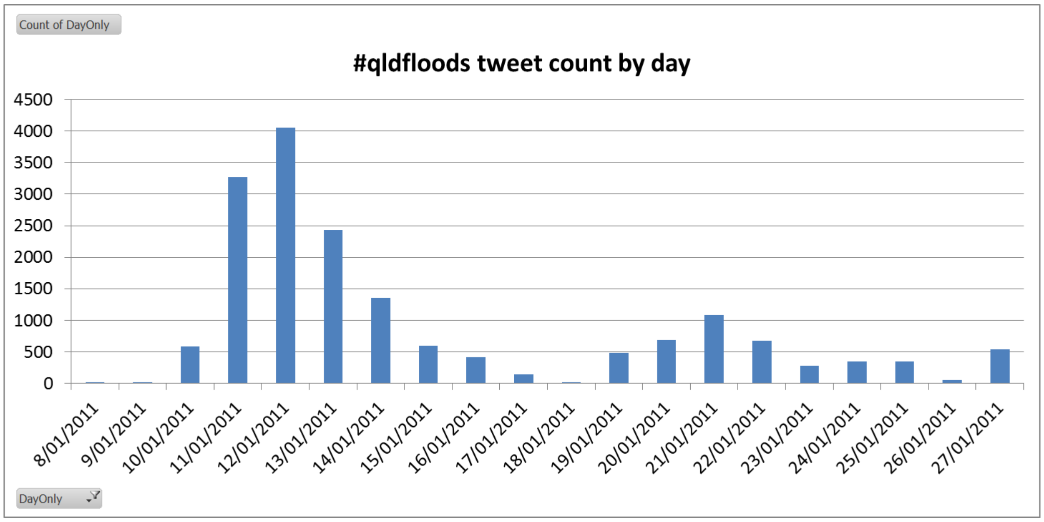


Figure 15: Count of tweet per day based on #qldfloods dataset excluding RT.

Based on that, total number of tweets selected for manual analysis were 1,373 tweets. From that list, 52 tweets were removed as they were duplicates (even though did not have RT) and therefore the total number of tweets evaluated was 1320. Phase one part one uses this sample for the coding and evaluation.

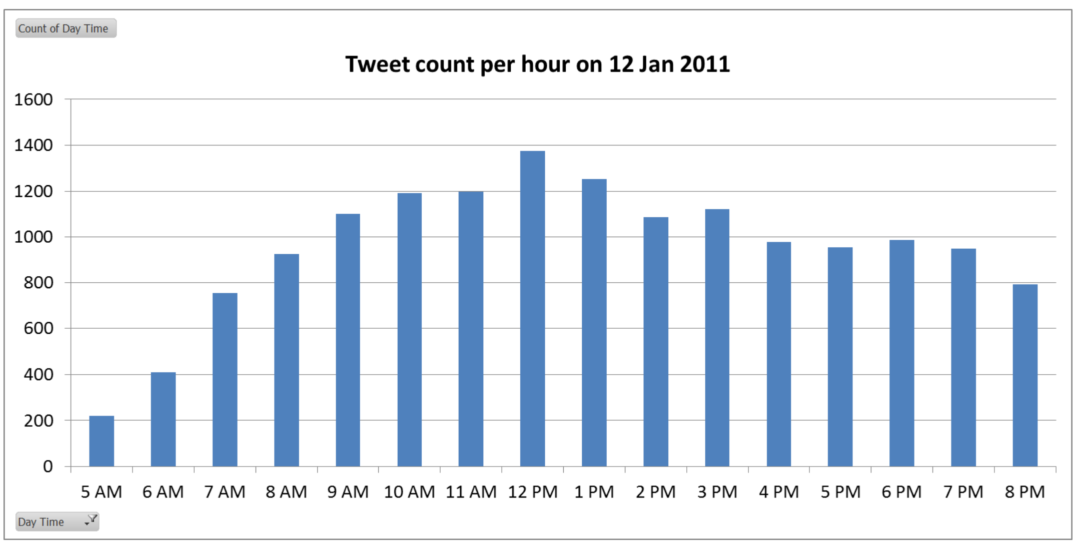


Figure 16: Tweets per hour on 12th January 2011

4.1.2 Sampling for phase one part two

Similarly to part one, as the 52,548 tweets from Yolanda dataset was too large for manual evaluation it was narrowed down to 382 tweets. This section describes that selection process and the differences to that used in part one.

Crowdcoding after natural disaster Although assigning multiple coder on the same dataset is an well established practice (Pipek, Palen, & Landgren, 2012; Starbird & Palen, 2012; Verma et al., 2011), utilising crowds to filter incoming tweets is gaining wider acceptance (Liu, 2014). For a number of years the research group at QCRI has been engaging crowds to evaluate social data (Meier, 2012). When a disaster happens researchers would capture the data from Twitter based on keywords and hashtags and then open that data to Internet users through system called MicroMappers. This is a part of their larger system known as AIDR (Artificial intelligence for disaster response) (Imran, Castillo, Lucas, Meier, & Vieweg, 2014). The system at first gathers tweets and other based on related keywords and hashtags and then filters them using various methods. Once the preliminary filter is done, QCRI team use crowdsourcing to identify which of these tweets are potentially relevant for emergency services.

MicroMapping for disaster response MicroMapping works similarly to the manual coding process where a few people read the content and categorise tweets into their respective group based on pre-defined categories. The difference is, instead of being coded by few people, the same content can be coded by hundreds of people.

Similarly to a manual coding approach, at the beginning each MicroMapper is given a one line description of the category meanings (Figure 17). Once they are familiar with the codes, they can press next to start evaluating the tweets. Each MicroMapper is then presented with a single tweet on the screen that they can categorise in any of the categories selected. However, to ensure inter-coder reliability each tweet is evaluated by more than one coder. Since the tweet selection is random, some tweets are evaluated more than others. *MicroMappers* Who then are these MicroMappers? Any person from around the world can go to the MicroMapping website to help classify tweets into categories. Participating in the site is voluntary and does not require the users to register, nor have any prior experience in digital volunteerism. According to micromappers.org "No need to register, and no prior experience or training required" and the objective is to "Click Your Mouse to support humanitarian efforts across the world" (Meier, Lucas, & Mack, 2013).

However according to Collins (2013), about 60% of these digital volunteers are academics, students, translators or journalists who already work in tech or humanitarian fields. When they know about the disaster, often through social media, they go to the website to offer help (Gilbert-Knight, 2013). Overall, MicroMappers are people who are experienced in digital disaster response even though they may not have formal disaster response training similar to emergency service managers.

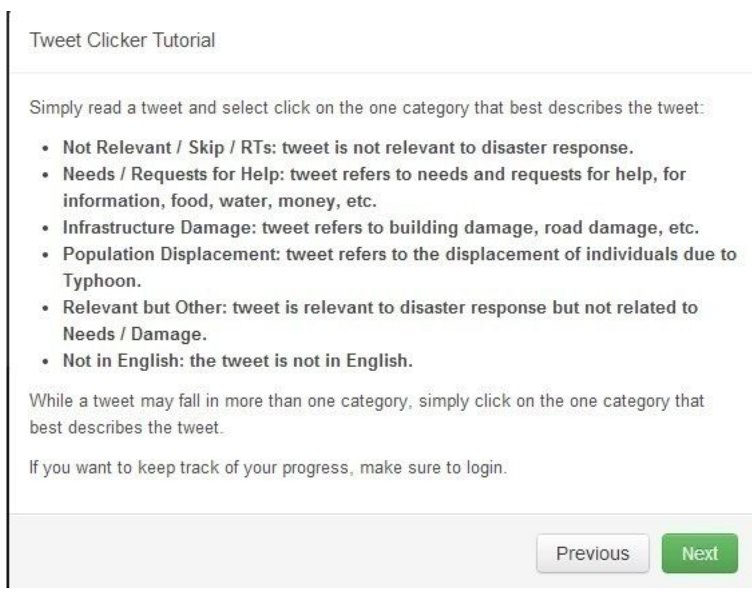


Figure 17: Tutorial at the start of MicroMapping explaining the categories

MicroMapping process   For the Yolanda dataset, each MicroMapper was given 1500 tweets to evaluate (Figure 18). However not everyone who participated evaluated all 1500 tweets. Therefore, even though a total of 90,000 clicks were generated through MicroMappers, not all the 26,664 tweets were equally evaluated. The evaluation resulted in 237,779 rows of data labelled with additional information such as taskID, category of the tweet selected by a MicroMapper in that task, and taskCompletionTime that suggests when the MicroMapping task was completed.

It is worth noting that, when a MicroMapper evaluates a particular tweet, the MicroMapper does not have any other information about the tweet (such as the user) except the fact that the tweet was composed recently. Therefore, it is likely that the information the MicroMapper has used to identify importance of that particular tweet is solely based on the text (and other symbols such as # or @).

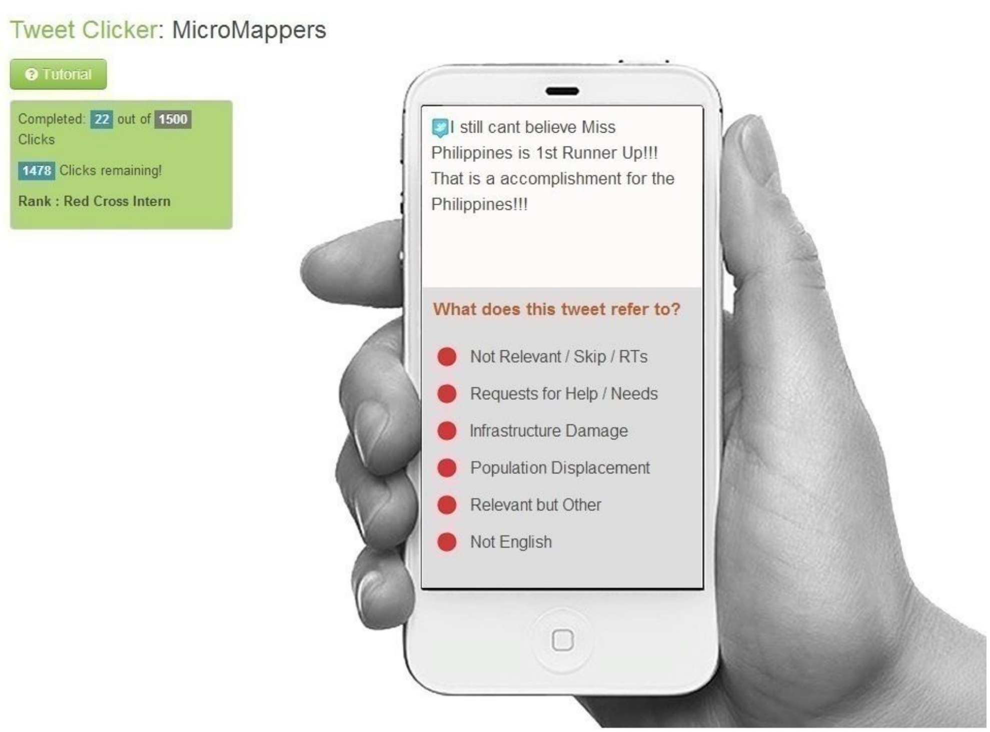


Figure 18: A sample tweet being evaluated via MicroMappers

Re-categorisation of the tweets For the purpose of analysing the Yolanda tweet dataset, among the six categories (Figure 18) three were regarded as relevant for emergency services. They are Infrastructure Damage, Request for Help and Population Displacement. Three others, Not relevant / Skip / RT, Not English and Relevant but Other were regarded as irrelevant for emergency services to identify disaster related tweets. Although in some cases the tweets that is classified as Not English may contain useful information, MicroMappers may not understand the language and therefore such tweets were classified as not relevant.

Agreement percentage calculation Inter-rater agreement is a commonly used approach in statistics to identify homogeneity among evaluators (Byrt, Bishop, & Carlin, 1993). Even though inter-rater agreement is generally used in small samples, such as Cohen's kappa, for two raters, and Fleiss' kappa for any fixed number of raters, Nowak and Rüger (2010) have extended this for crowdsourced tasks. Similar to Cohen's kappa, Nowak and Rüger (2010) found that more than 60% agreement between inter-raters is good and more than 80% agreement gets the best result.

Since a large number of coders have already marked these tweets as potentially relevant or irrelevant for emergency services, the objective was to find out which tweets all the MicroMappers agreed were relevant for emergency services and which are not, so that the difference between relevant and irrelevant tweets can be established.

Percentage agreement The single most striking observation to emerge from the data comparison was that MicroMappers agreed with one another when a tweet was not relevant for emergency services. As can be seen from Figure 19, most evaluators agreed on tweets that were not relevant for emergency services or were retweets.

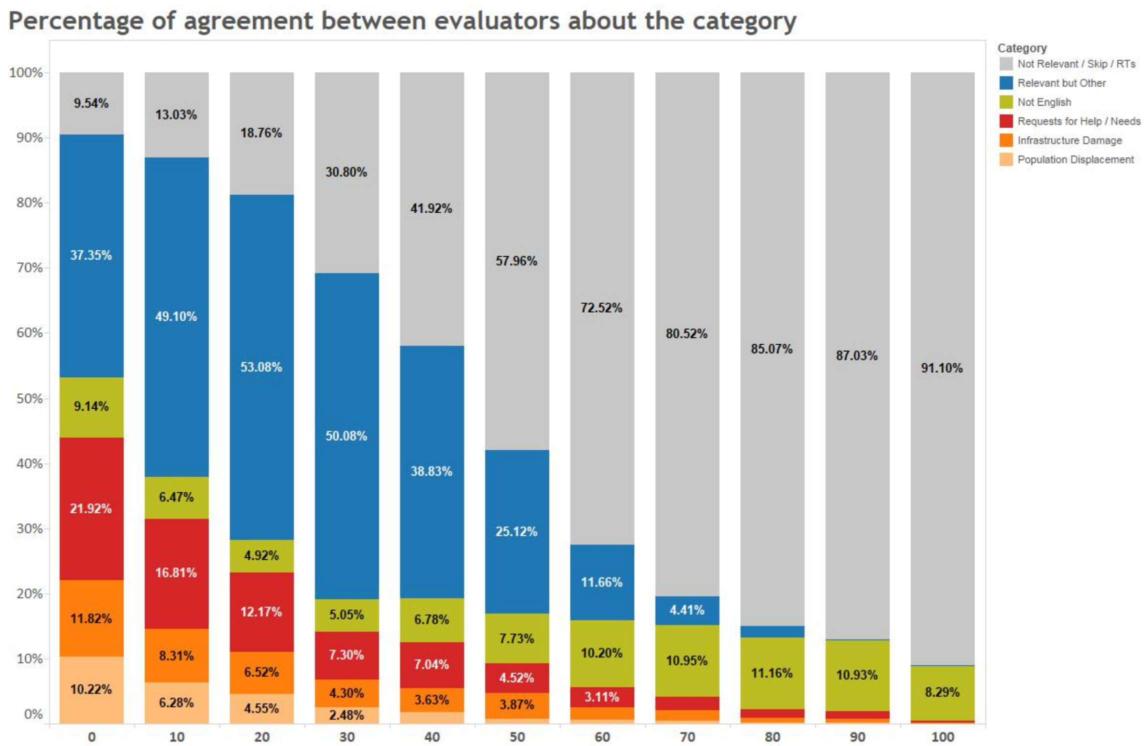


Figure 19: Agreement among MicroMappers whether the tweet belongs to a category

However, there was disagreement between evaluators when they were presented with a tweet that was somewhat useful. As it can be seen in Figure 19, tweets that belong to the relevant for emergency services categories, such as a Request for help, Infrastructure damage and Population displacement, did not achieve consistent agreement like the tweets in other non relevant categories. For example, the tweet "Bildt: Around ten Swedes missing in Philippines http://t.co/hDyLj45WJ2" was evaluated by 13 evaluators and was marked by six evaluators under Request for Help / Needs and five evaluators under Population Displacement, one under Relevant but Other and one under Not Relevant / Skip / RTs. Compared to that, this tweet "@ayeemacaraig daliii Kindly pls check my town #CarigaraPh no news from our relatives, no communication since #YolandaPH" was evaluated by 15 evaluators and 14 evaluators marked it under Request for Help and had an agreement score of 93.3%.

Selecting sample size Since only a limited number of tweets can be evaluated through manual close reading, tweets that had high number of agreement between evaluators were selected for analysis this part of the phase. Agreement scores of 80% and was chosen as the cut off point, as researchers have previously identified this score to produce the highest inter-coder reliability (Nowak & Rüger, 2010) .

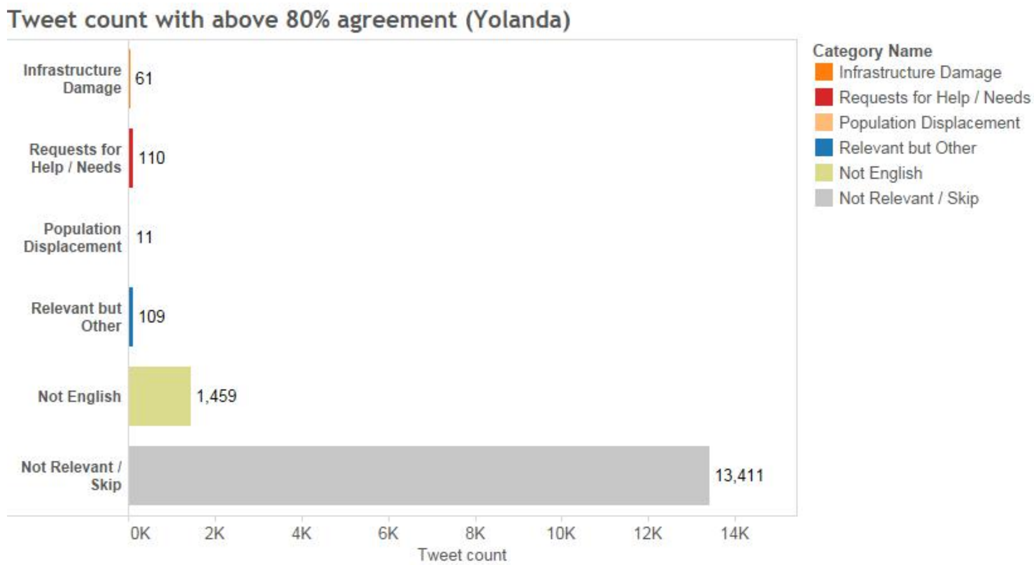


Figure 20: Number of tweets with more than 80% agreement between MicroMappers

Two types of tweets are selected for manual analysis. One type was the tweets that were coded as relevant for emergency services and the other the tweets that were not relevant for emergency services. Of the categories represented (Figure 20) amongst tweets which received 80% or more intercoder agreement, the vast majority were rated as Not relevant / Skip / RT. The top 200 tweets from Not relevant category were selected to find out more about why they are regarded as irrelevant to emergency services by MicroMappers. Tweets that belonged to Not English and Relevant but Other were also excluded as they fall under irrelevant categories. This leaves 182 tweets, distributed across the categories Infrastructure Damage, Population Displacement, and Request for Help that are likely to contain tweets that are relevant for emergency services. Based on the 80% agreement, there were 182 tweets available and these were selected for further manual evaluation in this project.

In conclusion, for the manual analysis phase, the sample size of the two datasets was reduced to a number suitable for close reading. For the #qldfloods dataset the sample size for qualitative phase was 1320 tweets collected using #qldfloods hashtag during six hours, from 9 a.m. to 2 p.m. on 12th of January 2011. For Yolanda dataset, the first part of the selection involved finding the percentage of agreement between MicroMappers. 182 tweets from three categories that are relevant for emergency services – Request for Help, Infrastructure Damage and Population Displacement had more than 80% agreement and therefore were selected for this phase. In addition to that, 200 tweets from Not Relevant categories were also selected for evaluation to investigate the common features that can be found from irrelevant tweets. After collecting the samples they were evaluated using coding and ranking, which is explained in the next section.

4.2 Coding and Ranking

In this first part of this phase, the objective was to gain deeper understanding about the contents of the tweets from both of the datasets to identify if they contained information that is potentially important for emergency services.

As mentioned in the Methodology chapter, usually the first step of content analysis is to create a coding manual and then use that manual to analyse the content. Additionally, for time sensitive contents such as disaster relevant tweets, researchers have also used ranking to create a point of differentiation (Huston, Weiss, & Benyoucef, 2011; Verma, et al., 2011; Vieweg, 2012). The following sub sections describe how both coding and ranking were developed in this research.

4.2.1 Coding categories and theme

The creation of a coding category is dependent on the research question (Saldana, 2012). Therefore creating appropriate coding categories play an important role in analysing contents and answering the research questions.

Since the purpose of this research is to identify information that may be relevant for emergency services, the coding categories were created based on the need of emergency services discussed in the earlier discussion on hazards, emergencies and disasters. In terms of method of coding categories, a descriptive coding method was used as it identifies topic from the content instead of summarising the text (Tesch, 1990; Wolcott, 1994). Although this method was developed to study longer form of text, in the context of evaluating tweets, it was deemed as most appropriate as it identifies the topic from the tweet. Based on the literature, the coding categories included three major themes: **Request, Report and Reaction**. These were broken into further coding categories as listed in Table 7.

Coding Categories	Sub categories	Description
Request for material support	• Request for food and water (RF) • Request for shelter (RS)	One of the first things people need after a disaster is food, water and shelter (Todd & Todd, 2011, p.4).
Request for medical assistance	• Requesting medical assistance (RM)	Sometimes some people are injured and some may seek medical assistance (Noreña, Yamín, Akhavan-Tabatabaei, & Ospina, 2011)
Request for information	• Request for information about person (RP) • Request for information about an area (RA) • Request for other information (RI)	People want to know about their family members (Si, Wang, Hu, & Zhou, 2011). People who are not in the area often look for information about that as well.
Request for other types of help	• Request for help (RH)	Various other forms of request such as request for help can be seen as well
Report of damage	• Reporting about public property damage (DP) • Reporting about private	To assess the damage of the area (Goyet & Morinière, 2006)

	property damage such as their own house (DH) • Reporting environmental damage (DE) • Reporting change in situation (DC) • Reporting injuries and deaths (DI)	
Reporting community behaviour	• Reporting about community mood, behaviour or situation (CB) • Reporting crime that happened after the disaster (CC)	False information, criminal activity and various other issues dampen community mood after a disaster resulting in action that may cause more harm. Tweets related to this can be useful for intelligence gathering
Reaction from community	• Reaction from community regarding emergency service efforts (RE) • Reaction or response from community, community efforts, advice (RC)	To assess the community mood in order to gauge if a community might be doing something that is not intended (e.g., going to a shelter centre using a road that is prone to flash flooding) (Harrald, 2006). Knowledge of crime is necessary for mobilisation of resources. Identifying the first responders can help emergency services to engage people who have been doing the hard work at the beginning and not alienate them (Telford, Cosgrave, & Houghton, 2006).
Other	• Spam or marketing message (OM) • Spiritual messages (OS) • Greetings and thanks (OG) • Narratives that may not be directly useful for emergency services (ON) • News and reports (OR)	A lot of messages in social media are not related to the needs of emergency services in the context of a disaster even though they might be welcomed in other instances. Spiritual messages and greetings are commonly seen but not useful for emergency services purposes. Similarly, news and reports are not very useful for emergency services

Table 7: Coding categories based on the need of emergency services

T the type of contents falls under each of the coding sub categories are described next.

RF - Request for food and water Where people ask for food and water. After a major disaster it is common for people to run out of food and water.

RS - Request for shelter Where people inform about loss of places to live, or ask if anyone has a place for them as their house is currently disaster struck and unliveable.

RM - Requesting medical assistance Where people seek for medical assistance as they or someone they know are injured. As this requires different emergency services to respond (e.g., ambulance), this is categorised under different category.

RP - Request for information about person One of the first things many people do after a disaster is to look for their family members. In many cases these are relevant tweets for emergency services to assist in looking for people who might still be missing in an area.

RA - Request for Information about an area Tweets that ask about the conditions in a particular area. While these tweets are not the highest in priority for emergency services, they can be used to get update about the latest changes in a situation that may not have been reported before.

RH - Request for help Sometimes people can call for help in situations that are not life threatening. For example, someone calling for help to give them a hand in moving something. If a lot of people are asking for similar help it might be relevant for emergency services to look into it in order to find patterns.

DP - Reporting about public property damage Information about damage to public property is one of the most crucial for emergency services because people may be trapped in public buildings.

DH - Reporting about private property damage By collecting information from people updating about damage to their private property emergency services can identify the seriousness of a situation in a given area.

DE - Reporting environmental damage Report about environmental damage contains information about surroundings such as trees falling and blocking roads, water tanks or electric poles getting damaged, and road flooding. These can inform how devastating the disaster was.

DC - Reporting change in situation Tweets reporting such as mention of a sudden flash flood or a tornado has just occurred.

DI - Reporting injuries and deaths Tweets that report about death can be used to identify the loss of lives in an area. Report about injury can indicate potential medical emergencies.

CB - Reporting about community news, mood, behaviour Sometimes it is necessary to know about community mood or behaviour in order to mobilise appropriate resources.

CC - Reporting crime that happened after the disaster Knowledge of criminal activity in an area can be useful for the safety of the emergency workers.

RC - Reporting community efforts and advice Reporting about community efforts that can range from clean-up volunteers, food providers, to wifi and electricity providers

RE - Reaction from community regarding emergency service efforts Getting feedback quickly is essential for emergency serves as it can help them to identify if their efforts are in the correct place.

OM - Spam or marketing message Messages that uses the hashtag or keywords but has no relationship with the event

ON - Narratives that are not directly useful for emergency services *It is common to see a lot of personal narratives during natural disasters.*

OS - Spiritual messages Messages that are spiritual in nature, such as asking people to pray for victims.

OG - Greetings and thanks Tweets that come from well-wishers wishing disaster victims.

OR - News and reports Many people tweet links from news reports in social media. Although they are useful for the general public awareness of the situation, news reporters often learn about the incident from emergency services. Therefore they are often not rekevant for emergency services.

4.2.2 Ranking of information

Not all areas get equally affected in a natural disaster. Sometimes some areas can have repeated waves of disaster or sometimes the situation may suddenly get worse. Therefore knowing the current situation is a top priority for emergency services. Even though the coding schema identified in Table 7 can be used to identify if the tweet contains information that may be needed by emergency services, it only identifies if the tweet contains information without creating an order of priority.

Identifying urgency and specificity from tweets Therefore, in addition to identifying the topics, to identify the level of importance it is common to add a magnitude coding to the coding category (Saldana, 2012). Generally in natural disaster situations, such prioritised information is gathered by designated emergency services personnel and then channelled to central information control who determines the severity of the information (Iakovou & Douligeris, 2001). For the purpose of this research, the magnitude can be determined based on the urgency and specificity of the tweet. A tweet mentioning "water coming to the house at Kelvin Grove right now" is more relevant for emergency services than "water is rising" – which is neither urgent nor precise. Thus the magnitude coding is ranked (Table 8) based on their **urgency** or **specificity**. If the tweet contains both urgent and specific information, it is ranked higher compared to another tweet that may contain either or have neither.

Criteria	Value	Description
Rank	4	Definitely urgent and/or specific
	3	Moderately urgent and/or specific
	2	Somewhat urgent and/or specific
	1	Neither urgent nor specific
	0	Spam, unclear relationship with disaster

Table 8: Ranking of tweets

Coding for other content features The patterns identified in the manual analysis phase were used as the basis for designing an automated evaluation algorithm in the automated analysis phase. Therefore, the components that make a tweet potentially urgent or specific needed to be broken into specific features. These components can consist of the text, metadata or metadata extracted from the text. Among the data and metadata that can be extracted from tweets, text and especially keywords, have been the dominant component researchers use when analysing Twitter as well as other web based platforms (Brin & Page, 1998; Burgess & Bruns, 2012; Kim et al., 2013; Robinson, Power, & Cameron, 2013; Williams, Terras, & Warwick, 2013). In terms of natural disasters, other metadata such as images (Aggarwal, 2011; Gupta, Lamba, Kumaraguru, & Joshi, 2013), location and named entity (Finin et al., 2010; Li et al., 2012; Liu, Wei, Zhang, & Zhou, 2013), and users (Kumar, Morstatter, Zafarani, & Liu, 2013; Pennacchiotti & Popescu, 2011). Since both location names and image URLs can be identified from the text itself during a manual reading, they were selected as features to extract.

For the purpose of this part of the phase three specific features – keywords, image URL and location names were selected to evaluate. The method applied was to read the tweets and give it a ranking number (between zero and four), identify which coding category it belongs to and if it contains an image, location names and keywords. How this was applied to the dataset is described in the next section.

4.3 Part One: #qldfloods dataset

The following sections discuss the findings from the #qldfloods dataset after applying coding categories and ranking (as detailed in Tables 7, 8 and 9) shows an example of the process of how each tweet was read and given a rank and code.

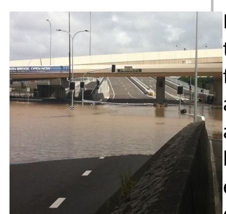
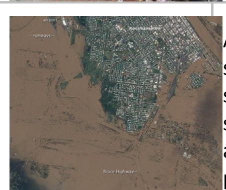
Tweet	Rating	Code	Keyword	Location Name	Image	Comment
Riverside walkway flooded and rising looking towards Friday. Where I'm standing will be under soon http://twitpic.com/3p9ax8 #qldfloods	4	DC	Flooded, rising, soon, standing	Yes, Specific		Uses urgent words such as “soon”, “rising” along with location. Picture shows moving water
Cnr Coro Drv and Hale St. Go-Between bridge on ramp #aquapocolypse #qldfloods http://twitpic.com/3p9jmq	3	DE	none	Yes, Specific		Picture shows the area being flooded although there are no keywords except names of places.
http://twitpic.com/3p8iqz Have just seen first hand the aftermath at Toowoomba. Hard to believe the sheer force of flash flood #qldfloods	2	DH	Seen, aftermath, flash, force	Yes, Specific		While it shows the damage done by the flash flood, the flood is not there now
Amazing image from NASA of the flooding in Rockhampton: http://bit.ly/hSddi0 #QLDfloods #fb	1	ON	Flooding, image	Yes, General		Although a satellite view shows the status, it is not a matter of priority
Get your tickets to @ladisputeband @danmanganmusic @sparkadia or whoever else you wanna see TODAY on @OzTix!! www.oztix.com.au #QLDFloods	0	OM	none	no	none	Not related at all

Table 9: Ranking and other metadata analysis of the tweets

As it can be seen from Table 9, when the tweet was showing urgency and providing temporal information, such as soon or rising, it was given a rank of four. Compared to that, despite the tweet about #aquapocolypse including a photo regarding damage, the urgency could not be determined and therefore the rank was lower. Similarly, tweets with NASA had a lower rank due to a lower level of urgency. It is necessary to note that, although all the tweets included in the Table 12 had location names, it was not the case for all tweets.

Both coding and ranking of the #qldfloods dataset was done by the researcher. As discussed earlier, even though coding is generally done in a team to reduce the coder-specific error and to improve reliability, when the objective is to gain an understanding of the whole dataset in order to perform future experiments, sole coders are also employed (Burant, Gray, Ndaw, McKinney-Keys, & Allen, 2007; Strauss, 1987). In such situation where solo coding takes place, Saldana (2012) suggests the sole coder consult a mentor or supervisor or even a colleague during the analyses process as a way of validating the findings. Therefore the results were analysed periodically by the thesis supervisors. At the end of this part of the phase, a number of criteria were identified that fulfil the requirements of emergency services and could be considered as important.

In conclusion, the key focus of understanding the disaster relevance of a tweet is to find the value of the tweet for emergency services. Even if the tweet had the word "soon", and it suggests urgency, it might already be well known and therefore not have a strong value for emergency services. On the other hand, having a photo or a location that is not known but that has recently been damaged is extremely valuable for emergency services. Since such understandings are qualitative in nature, the objective of this phase was to identify any specific features that might be extracted automatically through quantitative methods. The next section presents the outcome of the manual analysis for the #qldfloods dataset to identify which features can be used in the design of an automated algorithm for detecting potentially disaster relevant tweets (described in the following chapter).

4.3.1 Distribution of coding categories

The first set of analysis examined if the tweets contained more noise than relevant tweets. That is, they were tweets that are not related to the disaster, thus making them irrelevant for emergency services. Based on their ranks in Figure 21, it can be seen that the largest number of the tweets (1062 tweets) were ranked at number one, the lowest rank of importance. This is similar to the findings of other twitter researchers (Imran, Elbassuoni, Castillo, Diaz, & Meier, 2013a; Thaiprayoon, Kongthon, Palingoon, & Haruechaiyasak, 2012; Tonkin, Pfeiffer, & Tourte, 2012) who found that the bulk of tweets after a natural disaster, and in other catastrophic situations, contain mostly narratives that are not very useful for emergency services purposes.

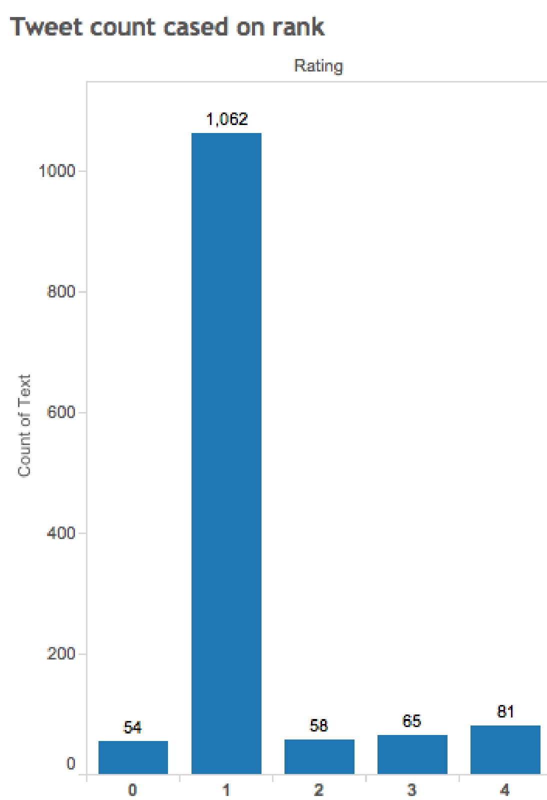


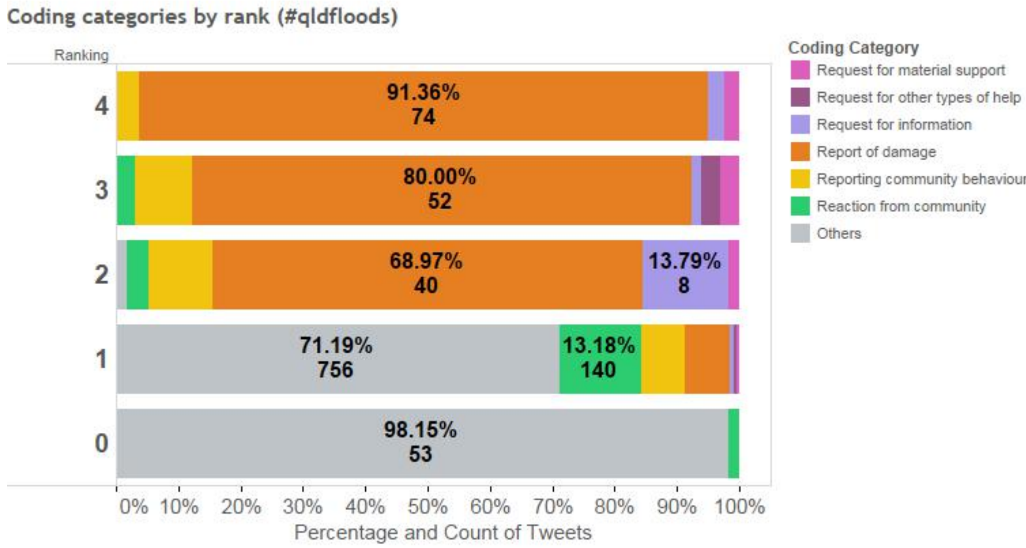
Figure 21: Total tweets based on their ranks from sample tweets

Distribution of coding categories based on rank Figure 22 displays the distribution of coding categories and sub categories in their respective ranks. As detailed earlier in Table 7, three themes, Request, Report and Reaction were identified as relevant for emergency services from synthesising the literature. The objective of this analysis was to find how often these codes appear in each ranked groups.

Based on the Figure 22, it can be seen that in the tweets from the #qldfloods dataset that were selected for evaluation, reports of damage were significantly higher than other relevant categories. In that category, the largest was reports about environmental damage where people tweeted about their surroundings. This was followed by Change in Situation where people reported about rising water.

There were minimal tweets related to Request for Material Support such as food, water, shelter and among the requests one of the prominent was asking for shelter for animals: “URGENT PLz REPOST Fairfield RSPCA is going under water anyone who can take in any animals please call (07) 3426 9999 #qldfloods #lime”. This supports the need to include tweets related to animals as relevant for emergency services as identified by Heath, Kass, Beck, and Glickman, (2001) with regards to people not wanting to evacuate while leaving their pets behind.

Reports about the community and their reaction towards the effort of emergency services was identified as relevant for emergency services in the coding categories listed in Table 7. Based on the findings presented in Figure 22 it can be seen that it was not a significant component in the highest importance ranks. While some of the tweets such as “power cut off in Highgate Hill. when will it be fixed? no idea. #qldfloods”; is somewhat useful indication of people’s mood in an area, “I feel so helpless. #qldfloods stay strong Queensland!” does not have actionable information for emergency services. Based on the distribution of the coding categories it can be suggested that finding Report of Damage tweets should be a priority in the automated analysis as tweets from Report of Damage were most prominent in the highest ranked tweets.



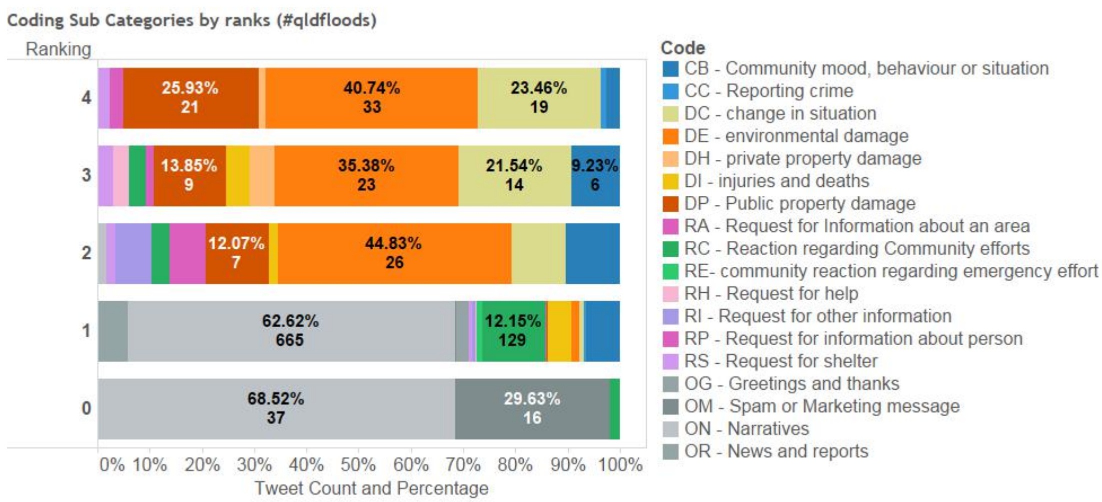


Figure 22: Distribution of tweets in their coding categories and sub categories by rank (#qldfloods)

4.3.2 Occurrence of specific information

As mentioned earlier, specificity and urgency (Table 8) were the driving force behind the ranking. In order to assess the frequency of specific information occurrence, the name of location and images were noted while evaluating tweets. The most common finding was that tweets with highest ranking had either a name of a place or a picture or both. As it can be seen from Figure 23, tweets that were ranked three and four had a high percentage of image and place names. Of those ranked four, 95% of the tweets had either location names or images compared to rank one and two where only less than 30% of the tweets had either of the location or image. **This is a significant finding as it suggests that if a tweet contains a location name or an image it is likely to be a tweet relevant for emergency services.**

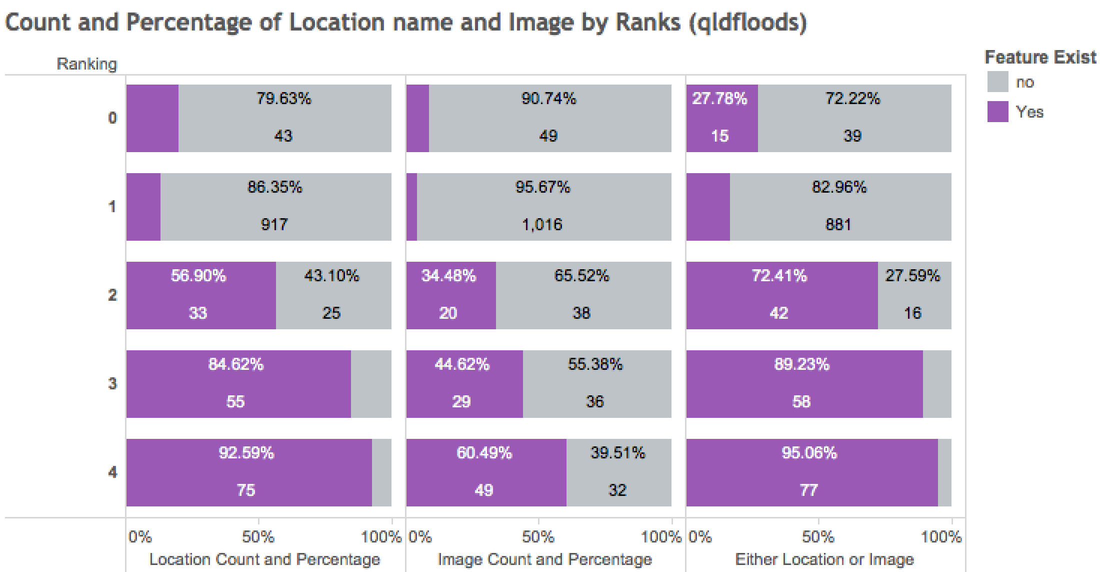


Figure 23: Percentage of location names and Image in the tweets based on ranks (#qldfloods)

Furthermore, another interesting observation from this dataset is that some Twitter users tried to combine the hashtag mechanism of Twitter with the name of places to increase prominence as well as make the tweet clickable. For example:

> *#Caboolture residents hardest hit by #QldFloods are now counting the cost http://bit.ly/fpc5Q5 @QuestNewspapers*

> *#Adelaide let's come together and help the people of #qldfloods. There's a 'Shoe Boxes of Love' Flood Appeal set... http://fb.me/OWxpSwyR*

Although these tweets were not relevant for emergency services, they certainly serve as a marker to identify name of a place. This use of place names with hashtags was a novel attempt to highlight a location in 2011 even though it might have become common knowledge in 2015. Even though there were only five such instances where people used a hashtag in front of the location name, it was an interesting attempt to highlight a name of a place. In terms of image, a lot of the images were hosted on third party websites such as twitpic or yfrog. This is likely to have changed as Twitter has introduced its own feature for embedded images, but the presence of images remains an important marker to consider.

Specific information by code It is perhaps not surprising to see that Report of Damage had the highest number of images while both damage reports and Request for Information had a high number of location names (Figure 24). Most tweets that enquired about information wanted to know if a specific place was still unaffected by the flood or if a road was still functioning.

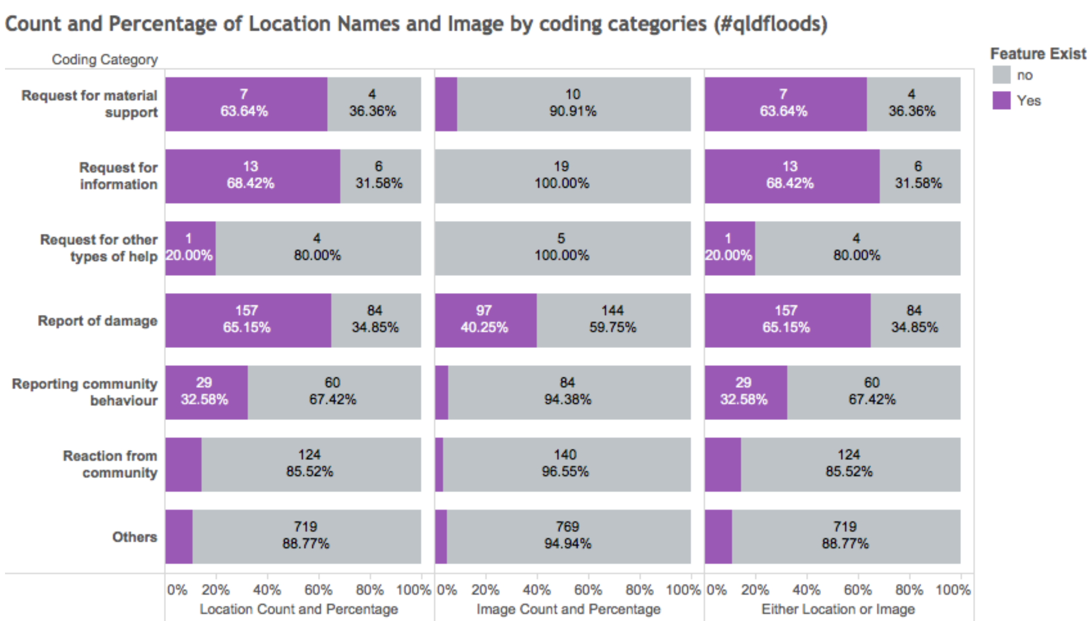


Figure 24: Percentage of named entity and image in the tweets based on codes (#qldfloods)

However relevant information do not always contain photo. For example, when people tweeted about crime, often they did not take a photo. An example can be seen in this tweet: , *"@FamePR SOMEONE LOOTING CATTLE IN IPSWICH AREA!! #qldfloods"* is a relevant tweet for emergency services even though it did not have a photo posted to prove the crime. The mention of the criminal activity is often sufficient to alert emergency services.

4.3.3 Keywords

Words are an integral part of Twitter (Jansen, Zhang, Sobel, & Chowdury, 2009). Although word sense disambiguation (WSD) is a known problem for any automated analysis of documents (Banerjee & Pedersen, 2002), especially tweets (Bakshy, et al., 2011), in the manual phase the attempt was to distinguish between keywords that are likely to be an indicator that a tweet is relevant to emergency services, and those that may also occur frequently in other contexts.

Coding Categories	Notable Keywords
Request for material support (RF, RS)	Seeking, help, flood, animals, roof
Request for medical assistance (RM)	None as no tweets were in this category
Request for information (RP, RA, RI)	Anyone, contact, current, have, know, my, mum, old, power, safe, situation
Request for other types of help (RH)	Animal, anyone, can, dog, evacuate, looking, offer, organise
Report of damage (DP, DH, DE, DC, DI)	50 cm, across, another, area, at, basement, been, braces, bridge, brim, closed, closes, Coming, corner, crocodile, debris, destroyed, direction, door, down, ferry, filling, flash, flat, floating, flood, floodbound, flooded, flooding, flow, from, full, getting, gone, good, height, high, higher, hour, house, indistinguishable, lake, large, later, line, low, massive, meant, midday, near, nearly, next, no , now, on, our, out , peak, quickly, raw, rising, river, riverside, roads, rise, scene, second, serene, sewage, someone, soon, spewing, still, street, surging, swallowed, terminal, tide, time, towers, under, underwater, water, waterfront, were, worst
Reporting community behaviour (CB, CC)	Creeping, donate, evacuating, fever, flood, grim, helpless, homes, information, located, looting, lost, morgues, near, polluted, power, river, safe, sandbag, shot, submerged, temporary, washes, water, wrong
Reaction from community (RE, RC)	Amazing, anyone, asking, avoid, back, call, charger, check, donate, donated, extraordinary, floodwater, follow, great, help, list, needs, offer, out, pack, people, phenomenal, photo, picture, please, proud, really, safe, session, suffering, superb, together, try, volunteer, when
Others (OM, OS, OG, ON, OR)	According, amazing, business, buy, comparisons, ideological, God, lord, love, mercy, miracle, pray, prayer, price, purchase, sexy, striking

Table 10: Common keywords in #qldfloods dataset based on their coding categories

Contrary to the previous two sections, the distribution of keywords was not the key focus of this section, which was instead to build a dictionary of keywords that can be used in automated analysis in next Chapter.

Many of the high ranking tweets had keywords that were active verbs such as “rising”, “flooding”, “creeping”, “floating”. This finding of action words is similar to the findings of Vieweg et al. (2008). Some tweets also mentioned current situations such as the word “now”, “near” as well as “quickly” to indicate the urgency level.

Many of the tweets used words such as “basement” and “under” to suggest the status of the flood. In addition, there were also mentions of family member related words. For example “Can anyone on #BribieIsland pls confirm conditions? Cannot ctc my 96 year old mum at Bongaree. Pls DM me #qldfloods”. Therefore words related to family members were included in the list of keywords to consider.

However, just the existence of the words did not necessarily make the tweet relevant for emergency services, which reinforces the WSD problem. For example, these two tweets:

> *“Fucking floods! I'm donating to the qld flood appeal. Mother nature's a bitch. Stay safe everyone #qldfloods”*

> *“The river has broken at Yeronga according to ABC! #Qldfloods”*

Both had disaster related keywords such as “floods”, “mother” as well as action words such as the “river breaking its banks” at a particular place. However, one of the tweets was used to vent anger while another was a statement based on a report by ABC news. Therefore, having a potentially highly relevant word alone is not an indicator of the high importance of a tweet. At this stage of the research process, this selection is entirely qualitative and manual of course. This list of keywords are used in the automated analysis in following chapter.

4.3.4 Part-of-Speech

Part of speech has been used by various researchers to analyse crisis related twitter datasets (Corvey, Vieweg, Rood, & Palmer, 2010; Imran, Elbassuoni, Castillo, Diaz, & Meier, 2013b; Panem, Gupta, & Varma, 2014; Verma, et al., 2011). However each research project have focused on various parts of speech. Some have focused on verbs, while others looked at personal pronouns, adverbs, and determiners. In this research, tweets from both datasets were analysed to see the distribution of the part of speech in order to determine if a certain part of speech stands out in this dataset.

In addition to analysing various grammar based parts of speech, Twitter specific symbols such as @, # and RT were also analysed as they have been identified as potentially relevant markers for tweet identification by the Carnegie Mellon Ark-Tweet-NLP group (Owoputi et al., 2012). It should be noted that Ark-Tweet-NLP extends the Penn Treebank structure (Marcus, Marcinkiewicz, & Santorini, 1993) with a Twitter specific add-on.

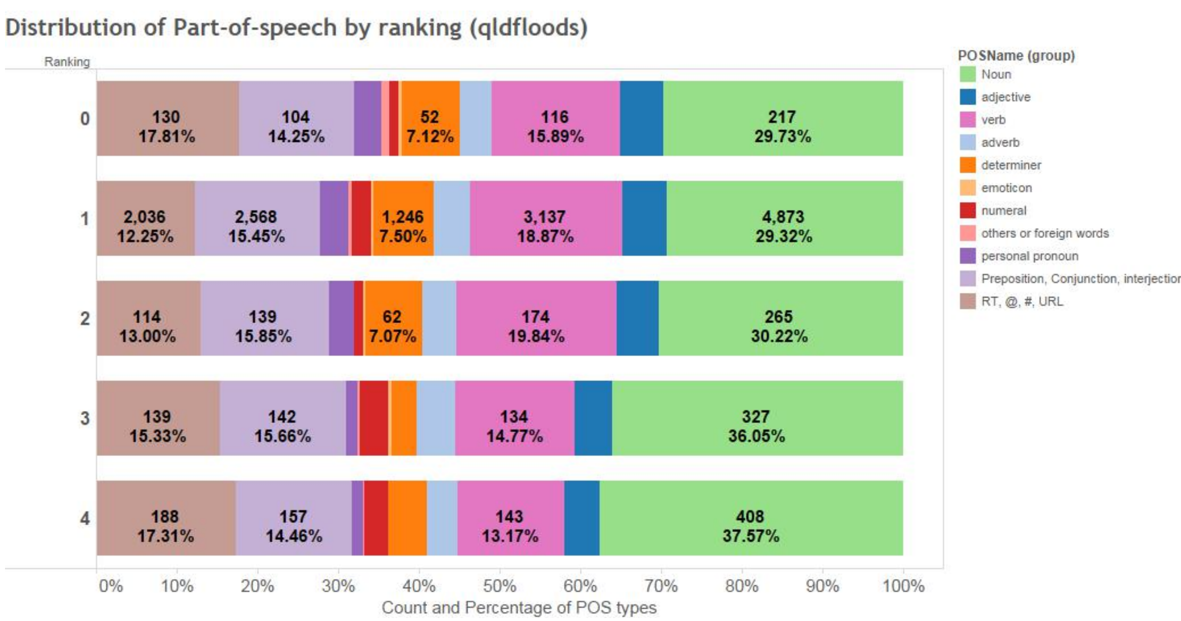


Figure 25: Distribution of parts of speech in their ranks from #qldfloods tweets

As it can be seen from Figure 25, nouns were equally common across all the ranks. Whether it was the relevant or irrelevant tweets, about 30% of the words were nouns. Similarly, the percentage of verbs was also similar across the ranks.

When this is analysed based on their coding categories, similar patterns can be observed. Relevant categories, Request, Report and Reaction had more adjectives and adverbs than the Other category. In terms of verbs, relevant categories had verbs with present and past participles such as “rising”, “spewing”, “surging”, “creeping” which are considered relevant for emergency services. The distribution from Figure 26 shows that none of the parts of speech were dominant.

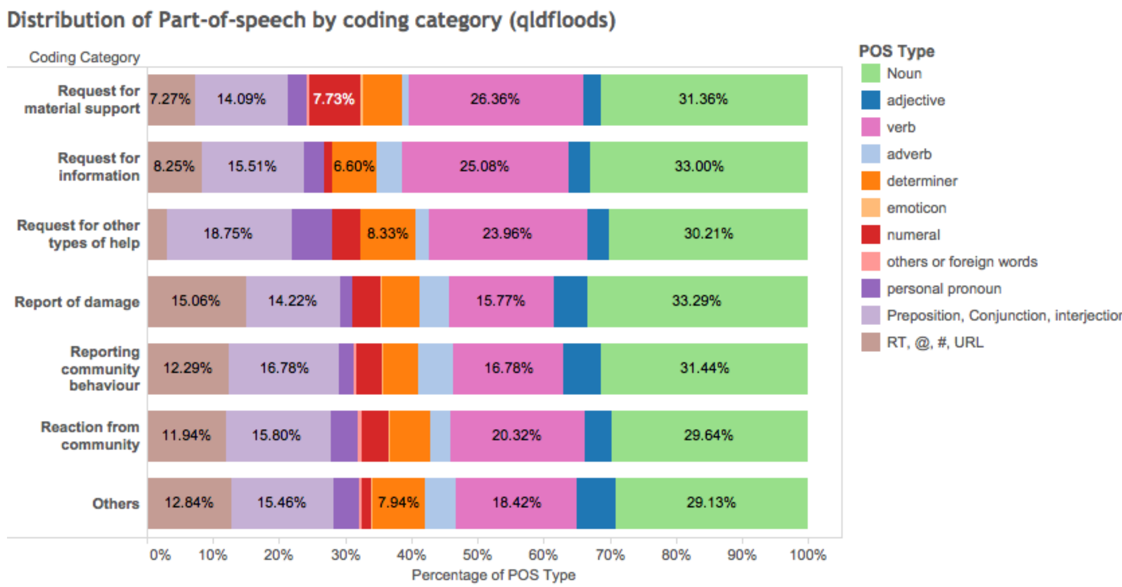


Figure 26: Distribution of parts of speech in #qldfloods tweets

These figures suggests that part of speech may not be an marker of relevance as it is difficult to identify a relevant tweet for emergency services based on their part of speech. Therefore it was not tested in the quantitative phase.

4.3.5 Summary of findings

This section summarises the findings from #qldfloods manual evaluation. There were a few novel findings from the #qldfloods dataset and some findings echoed similar results from other researchers.

> **1. High percentage of damage reports** The largest section of relevant tweets were related to damage reports. Among the damaged reports, environmental damage was the most reported damage. This could be due to the nature of the event or the evaluated dataset. Therefore this finding is compared in the next section with Yolanda dataset to find out if this can be used as a marker of disaster relevant features in tweets.
>
> **2. Image and name of place** More than 50% of the higher ranked tweets (three or four) had either name of a place or an image. Similarly, more than 50% of the tweets that were grouped under report of damage, request for material support or request for information also had a name of place or image in them. Based on the initial findings, it can be hypothesised that if a tweet has a name of place or image it is likely to be a relevant tweet for emergency services.
>
> **3. Patterns in the keywords** Although keywords can carry completely different meanings based on the context in which they are used, when keywords were grouped based on their coding category, certain patterns emerged. One pattern is specific to the words and the other is related to the part of speech.

When people were asking for information or requesting help, they tend to mention family members, their house or work place. When people mentioned a change in a situation, they used continuous tense more often than in other types of damage reports. When people tweeted damage reports, they often mentioned the distance of the water from a location, or the status of their house. When tweets contained spiritual words or greetings, they were often not useful for action by emergency services.

Preliminary rule set Based on these findings, a preliminary rule set to identify relevant tweets was developed. The common findings were that if tweets had pictures, or name of places, they were more relevant for emergency services. At the same time tweets that contained temporal information and words related to persons were also were considered more relevant. Furthermore, tweets that contained keywords that are closely related to the disaster such as "water", or the status of the water level were ranked high as well. Therefore based on this observation, the following rule set was identified for testing in the quantitative phase:

- If tweet CONTAINS (Name of Place OR Image) -> relevant for emergency services
- In order of relevance, Image > Name of place > keywords
- If tweet contains Desirable keyword > relevant for emergency services
- If tweet contains Undesirable keyword > irrelevant for emergency services

4.4 Phase One Part Two: Yolanda dataset

Although the Yolanda dataset was already categorised into six respective categories, to compare if the patterns in Yolanda tweets with #qldfloods tweets, they needed to match same category of #qldfloods. Therefore the selected sample tweets were re-evaluated and coded using the same coding categories used in #qldfloods to identify what type of codes. This section explains the findings of this process.

4.4.1 Distribution of coding categories

A similar manual process of reading tweets and grouping them in their coding categories and then identifying if the selected tweet samples contained location name, image, keyword and any other potential marker was performed at this part of the phase. Following is a description of the findings.

Coded tweets based on percentage agreed Of the analysed tweets, the distribution of codes in the Yolanda dataset were different than the #qldfloods dataset (Figure 27). Report of Damage was the dominant category in the #qldfloods dataset in high ranked tweets but in the Yolanda dataset it was present almost equally across all the ranks. The fact that the sample from the Yolanda dataset was already marked as relevant for emergency services was one of the major contributing factor for having reports of damage across all ranks.

In addition, the reason presence of other disaster relevant categories such as Request for Material Support and Medical Support in the high ranked Yolanda dataset, which was not present in the #qldfloods dataset. This distribution can be seen in detail in Figure 27. Among the report of damage tweets, reports of damage to the environment were the highest. A large number of tweets in this group had very useful tweets for emergency services such as "@micaelapapa: All paths out from our hotel along Candayog road in Palo, Leyte now impassable due to fallen trees and branches. #YolandaPH" and "Damaged electrical cables and fallen electric post along Rxs Blvd. #RoxasCity #Capiz #YolandaPH #HelpCapiz #RescuePH http://t.co/RKEr8s9RXa".

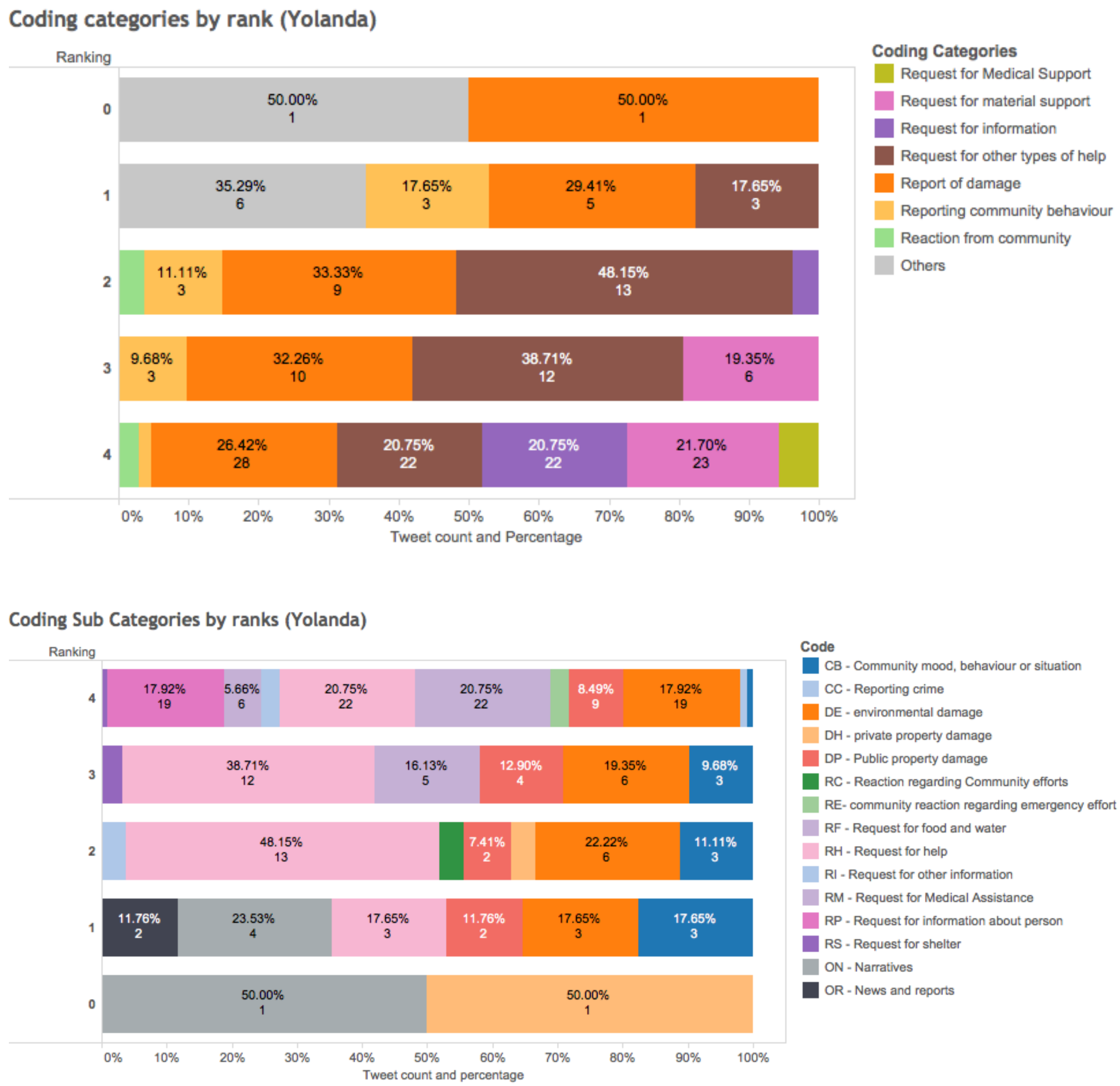


Figure 27: Distribution of tweets in their coding categories and sub categories by rank (Yolanda)

There were a large percentage of tweets (30% of the 182 tweets evaluated) that only asked for help without providing much detail about the type of help they required. For example, “@mateoguidicelli yes northern part of cebu is badly hit by #YolandaPH people there badly need help” and “@ANCALERTS Bantayan needs help!!! #RescuePH #BantayanIsland” both asked for help and had specific information such as location but did not mention what type of help they needed. Although these tweets provide a signal to emergency services that people need help, they need to respond and ask for further details about these tweets.

Compared to the #qldfloods dataset, Yolanda dataset had tweets regarding reactions to the relief efforts. For example, “@ancalerts #RescuePH please send help in Coron, Palawan now!!! No help is reaching them.” Is a good indication that certain area needs help and if they have not received help yet emergency services need to act on that.

Overall, as the tweets were already evaluated by many users and identified as relevant tweets, they had components that showed clear indications of being relevant. Furthermore, large numbers of tweets mentioned the area they were in; which is explained in further detail later in this section.

4.4.2 Occurrence of specific information

As it can be seen in the manual analysis of the #qldfloods dataset, specificity and urgency are two clear signs of relevance for emergency services. Therefore, to test if these tweets had specific information, location names and images were counted as well. And one of the most common findings was that almost all tweets had names of places (Figure 28). However, contrary to the findings from the #qldfloods dataset, the number of images in the tweets was incredibly low. One of the potential reasons for such low image count is the time the tweets were composed. Since the typhoon hit at midnight, people did not take photos and rather tweeted about their location. Therefore the percentage of tweets that had both name of location and images was extremely low because most tweets did not have images with them.

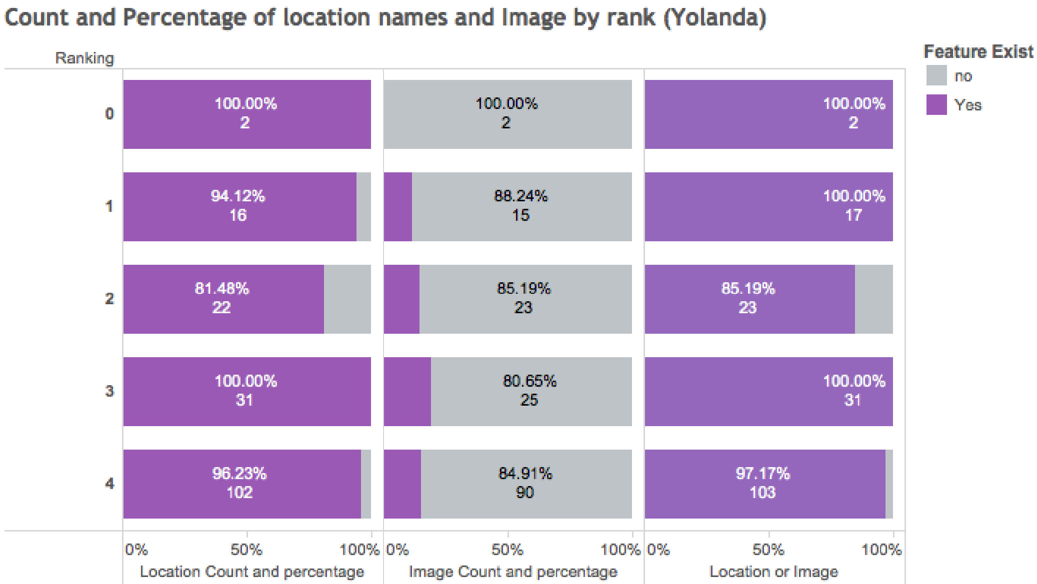


Figure 28: Count and percentage of image and location names in tweets by rank (Yolanda)

Specific information by coding categories By counting how frequently images and location names appear in the coding categories, it was found that similarly to #qldfloods, in the Yolanda dataset Report of Damage had high percentage of images (Figure 29). Although a closer look at the percentages suggests that the Other category (which contains irrelevant tweets) had the highest percentage of images, when it was evaluated further it was seen that the images where actually linking to tweets that were already categorised under Report of Damage. Overall, existence of image still remains an extremely relevant marker even though images were not as present as in the #qldfloods dataset.

In terms of location, as it can be seen from Figure 28 most of the tweets had mention of a location in them. Therefore in Figure 29, locations are present in almost all tweets regardless of the category. However, it should be noted that these tweets were already marked as relevant for emergency services by MicroMappers, therefore presence of location suggests that disaster relevant tweets are more likely to have mention of locations in them. Since image and name of place were both identified as important markers for emergency services, they remained as two features that were tested in the automated phase.

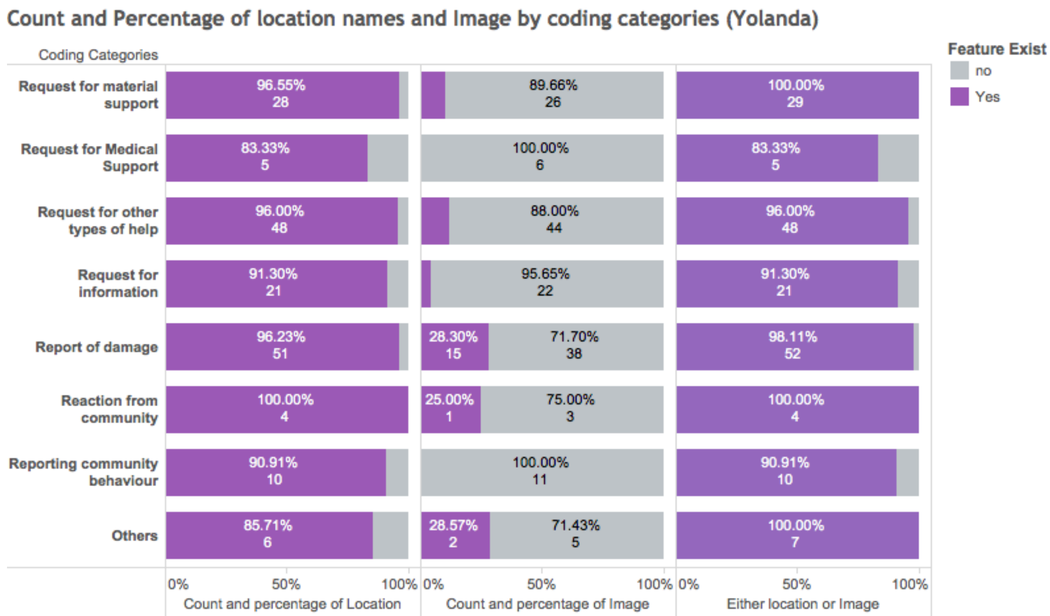


Figure 29: Count and percentage of image and location names in tweets by their code (Yolanda)

4.4.3 Keywords

As identified in the manual analysis of the #qldfloods dataset, keywords remain an important feature as it may indicate the context of tweet is in. The manually identified keywords from the different coding categories are listed in Table 11. Similar to #qldfloods, the listing reveals some specific findings. Common words such as "help", "please" were present in all categories by looking at the top keywords in these categories. There were variations of the words that included shorter, tweet-sized version of the words such as "pls", "plz". In addition to please, "building" was also mentioned as "bldg.". Table 11 lists keywords that were identified during manual evaluation where green were marked for those that would be desirable by emergency services to identify potentially disaster relevant tweets and red for undesirable keywords that were mostly present in the irrelevant tweet.

Coding Categories	Notable Keywords
Request for material support (RF, RS)	Also, any, badly, bodies, candles, damaged, dead, dire, electricity, everything, flashlight, food, from, goods, help, isolated, need, no, out, please, pls,

	received, relief, rescue, running, School, send, signal, update, water
Request for medical assistance (RM)	Please, need, medicines
Request for information (RP, RA, RI)	Any, anyone, anything, boyfriend, bring, check, colleague, contact, families, family, father, find, finding, for, friend, help, husband, knows, looking, lost, my, mother, out, people, plz, relatives, relief, rescue, son, still, update, yet
Request for other types of help (RH)	Please, send, relief, goods, dire, need, asking, help
Report of damage (DP, DH, DE, DC, DI)	After, almost, badly, blackout, bldg, block, bridge, cables, casualties, city, communication, damaged, destroyed, detach, disconnects, down, electrical, electricity, failed, fallen, falling, giant, help, hit, hitting, houses, impassable, knocks, leaning, lines, lost, need, number, outage, please, power, roads, roof, storm, strong, supply, their, trees, winds
Reporting community behaviour (CB, CC)	200, electricity, evacuating, evacuation, evacuees, families, forced, municipalities, out, residents, waters
Reaction from community (RE, RC)	Badly, haven't, help, need, now, please, reaching, received, send, yet
Others (OM, OS, OG, ON, OR)	Analyst, article, beautiful, believe, bless, breaking, calm, charts, discussion, glad, God, heart, hell, heroes, jobs, lord, love, mercy, mighty, miracle, pray, prayer, psalm, report, sex

Table 11: Common keywords in Yolanda dataset based on their coding categories

Infrastructure, environment and words related to help With regards to the words in the category Report of Damage, as this was a disaster related to strong wind, some of the keywords were “flying” of “roof” or “falling” of “electric pole”, which were relevant for emergency services. As it can be seen in Figure 29, a large number of tweets were about the damage of infrastructure as well as the environment and therefore uprooting of vegetation to block paths was considered as a relevant tweet. The pattern that emerged here from this limited set of tweets was that action words are generally specific to the disaster in context. When the #qldfloods dataset was analysed, the action words were “rising” (of water), “nearing” (of flood water); and in this dataset the words were related to the activity of wind. Furthermore, all the tweets that were grouped under infrastructure damage mentioned destruction in commonly known terms such as house, roof, and power line. Therefore, when using another disaster dataset, common behaviour and the action of that behaviour seems likely to appear in the tweets. This is tested in the automated analysis phase.

4.4.4 Part of speech

Findings from part of speech analysis of part two (Figure 30) are similar to the #qldfloods dataset. Nouns were present in all coding categories and often had similar percentages. Verbs, especially participles, were more visible in the relevant categories. In addition, prepositions and conjunctions were also present in the relevant categories.

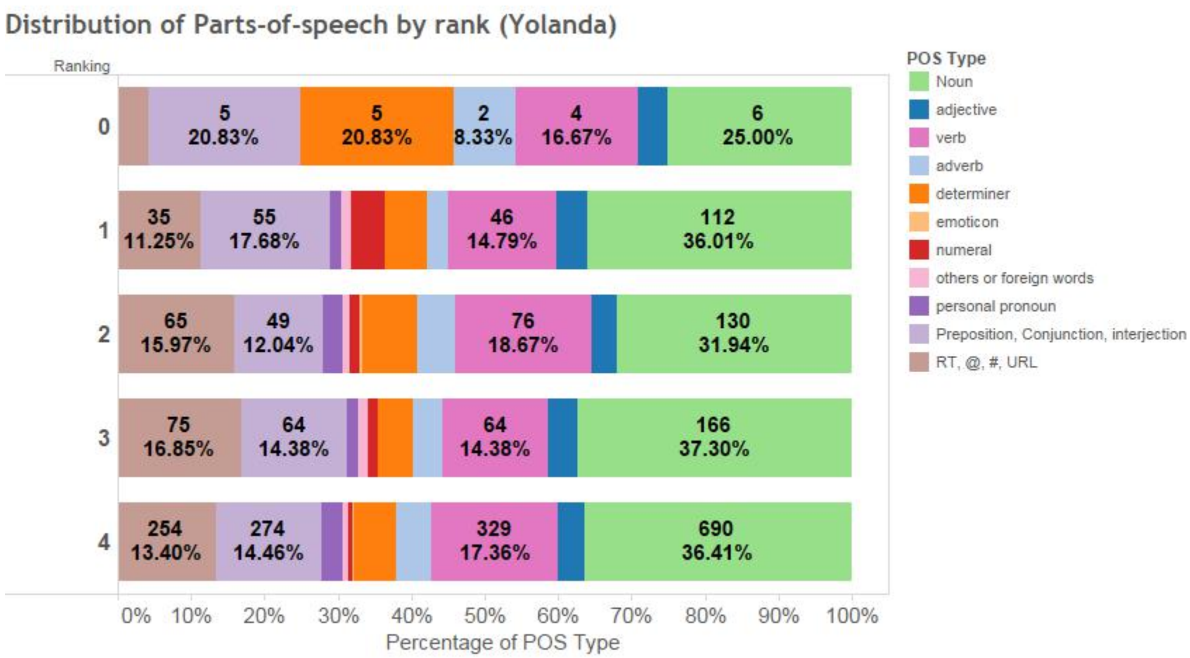


Figure 30: Distribution of parts of speech by ranks in Yolanda

Similarly, in terms of ranking the priority of information there was no obvious pattern (Figure 31). Similar to Figure 30, across all category nouns were present, which were followed by verbs. Surprisingly Report of Damage had a lower verb count compared to the other categories. Based on these findings, it can be suggested that part of speech is not a good determiner of importance. Hence, part of speech is not considered for phase two.

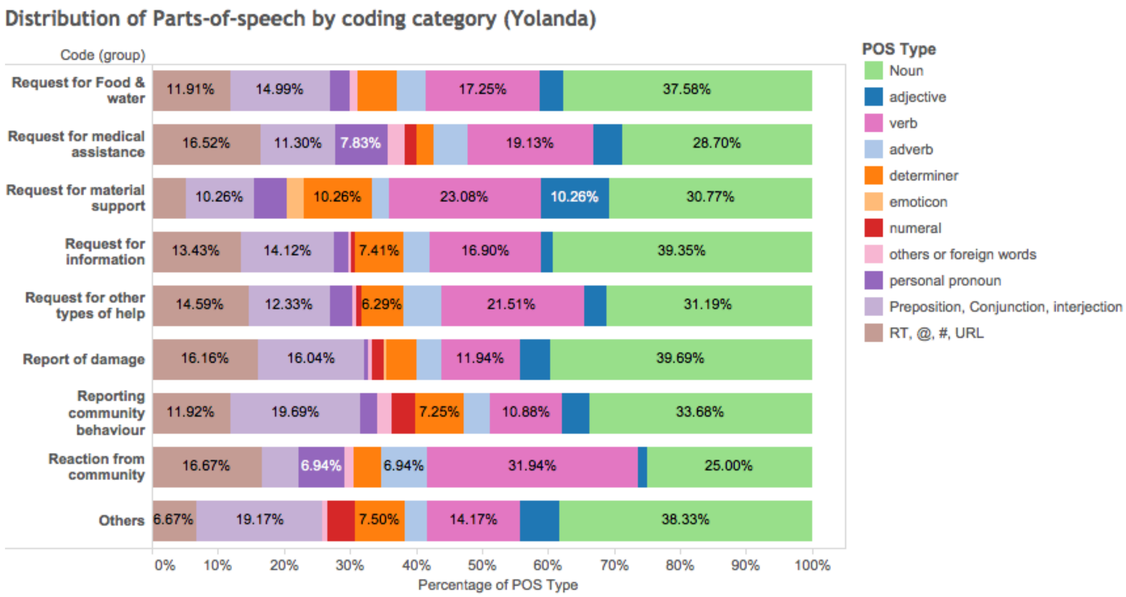


Figure 31: Distribution of parts of speech by coding category in Yolanda

4.4.5 Other findings

In addition to the findings discussed above, there were quite a few interesting qualitative findings that were different from those observed in the #qldfloods dataset. This section explains that those differences in detail.

Attempt to reach @prominent users One of the notable findings from the tweets in the Yolanda dataset were the attempts to reach prominent Twitter users which was not commonly found in the #qldfloods dataset. In two of the three categories, Damage to Infrastructure and Request for Help, Twitter users try to reach prominent users, celebrities and news organisations with the hope that their message will gain widespread attention. For example, one user tried to reach CNN international (@cnni) by mentioning the need for food and water with the hope that CNN will act on that. Although CNN did not reply to that tweet and the tweet was not retweeted by any other users (Figure 32), this tweet was deemed as relevant for emergency services by all 15 evaluators as Request for Help / Need with 100% agreement.

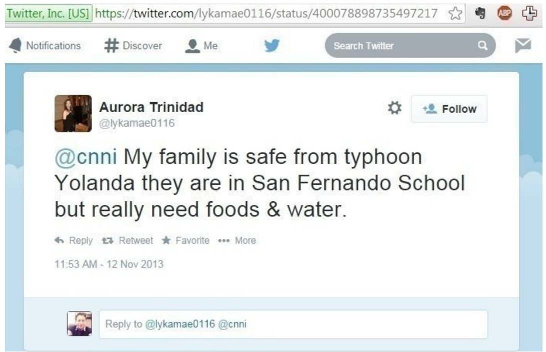


Figure 32: Twitter users attempt to reach CNN

This attempt to reach a prominent user was seen among many of the tweets evaluated in this part. While accounts such as CNN International is recognisable by disaster responders, many other accounts were prominent Twitter users or local celebrities who may not be obvious at first glance. As it can be seen in Figure 33, a number of users also tried to reach local media and local celebrities.

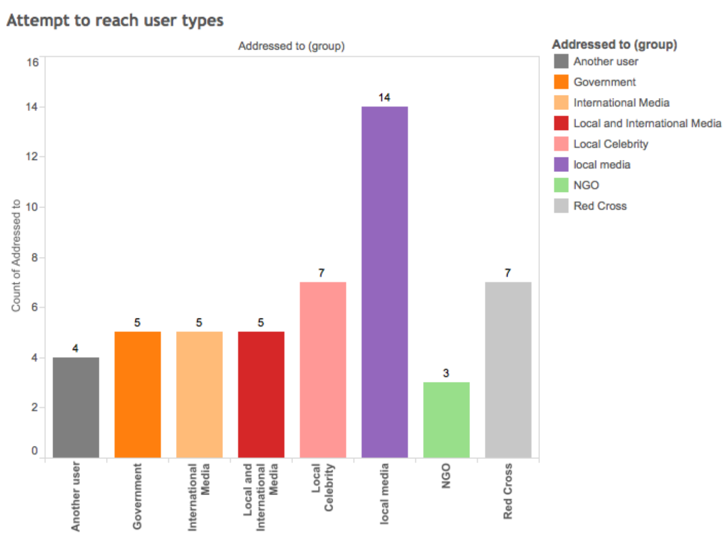


Figure 33: Types of people users were trying to reach

However, knowing which user is prominent and which is not automatically is difficult task. One of the ways this issue can be resolved in an automatic setting is by trying to identify if the user handle in the tweet has a large follower ratio. For example, a tweet was addressed to @micaelapapa (Micaela Papa) who is the senior correspondent of GMA news network from the Philippines. Even if she is not prominent worldwide, having more than 21,000 followers (at the beginning of

2014) suggest that she is potentially a prominent figure in Twitter. Therefore identifying if a tweet is trying to reach a popular user handle can act as a marker for emergency services.

Increasing use of #name of place – adding hashtags to amplify name of place
Compared to the #qldlfoods dataset where the number of hashtags used to magnify a place name was limited, in this dataset this was seen repeatedly. It was extremely common to read tweets such as “Power lines are slowly breaking and falling off. Roofs are about to detach #YolandaPH #mactan #cebu” where the user have not only used the hashtag to inform the audience about the larger area Cebu province, but also smaller area Mactan. By reading this tweet emergency services can not only identify that the area “Cebu”, which is more prominent province in Philippines is affected, it can also narrow down the location to “Mactan”, a densely populated island near Cebu that is not as widely known.

Therefore just by looking at the tweets it was possible to identify some of the areas that were affected; such as, Leyte, Capiz, Tacloban, Ormoc. However it is worth mentioning that not all the named places that had hashtags had only name of the place. Many of the hashtags were associated with other characters such as “PH”, which stands for Philippines. Although this is similar to the trend that is seen in naming other disaster hashtags, such as #qldfloods to suggest flood in Queensland, that usage of hashtag to suggest the name of affected area has not been seen widely in previous Twitter datasets.

#Pray-for-place hashtag Another common finding was the usage of “pray” in the hashtag in irrelevant tweets. All the tweets that had this word as part of their hashtag related to divine support and mental strength. Whether it was “Blessed Friday everyone! Keep safe!#PrayForThePhilippines” or “God bless the #Philippines #SuperTyphoon #Prayers”, all tweets with #pray were considered not useful for emergency services. However, identifying words inside the hashtag was not tested in this research as it increases the scope of this research.

Country name as hashtag Another common component of these tweets were the use of the word “Philippines” instead of being very specific such as “Cebu” or “Tacloban”. That could suggest that people who are tweeting those tweets are far away from the disaster and were well-wishes. However tweets that had both “Philippines” as well as the local name of place were relevant for emergency services as that was one way some users tried to get international media or celebrities to focus on the area.

4.4.6 Summary of findings

This section summarises the findings that were specific for the Yolanda dataset that was evaluated manually. They are:

1. High percentage of damage reports and requests for help Similar to the #qldfloods results, a high percentage of tweets were about damage reports. However, a large percentage were also requests for help. One potential reason for this is because the data was collected immediately after the disaster. Therefore, it was potentially filled with panic stricken tweets.

2. Image and name of place Almost 100% of the higher ranked tweets (three or four) had either name of a place or an image. This further confirms the importance of images and location names.

3. Patterns in the keywords Similar to #qldfloods, there was a pattern in the keywords. Seeking help was mostly associated with location names and help, asking for information was about a person, friend of family member, report of damage was about status of their own house and public property, along with words such as breaking and flying that are related to strong wind.

4. Part of speech In both #qldfloods and Yolanda it was found that it was not possible to identify disaster relevant tweets based on their part of speech.

Therefore part of speech is not included as marker for the automated analysis phase.

5. Emergence of new behaviour Certain new behaviours were also seen in this dataset. Two of the most notable were efforts to reach a prominent figure through their Twitter handle and efforts to amplify location names by putting hashtags in front. In addition, analysing the location names demonstrated that tweets that were about very specific locations (such as Cebu) were more relevant for emergency services than tweets that mentioned the country in general.

The next section summarises findings from both part one and part two to create guidelines for next step, the quantitative phase.

4.5 Summary of Findings from Manual Analysis

In majority of previous disaster related Twitter research the aim was to identify what type of information is available in Twitter and group tweets in their respective categories. While this has resulted in identifying that Twitter can be used to harness intelligence for emergency services, emergency services have been slow in adopting these findings. Therefore this chapter addressed the primary research question about relevant information for emergency services. As relevant is a subjective term, it used qualitative methods to create coding categories (see Table 7) by synthesising literature that groups key needs among disaster response organisations. The coding themes developed were:

1. **Request** - which includes requests for material support, medical assistance, information or generic requests for help.

2. **Report** - which includes reports of damage (public, private or environmental), change in situation, about community, effort from people, crime, injuries and deaths.
3. **Reaction** - which includes tweets from the community regarding emergency service efforts so that emergency services can identify if their effort is in the right place.
4. **Other** - Anything that does not fall into these categories.

Using these coding categories and samples from two different datasets (#qldfloods and Yolanda) close reading was used to identify the existence and distribution of the categories in the tweets. The key findings that arose through this coding are summarised below.

Overall codes and their distribution Among the three themes – Request, Report and Reaction – the majority of tweets were categorised as damage reports in both the datasets. In the Yolanda dataset Request and Reaction (Figure 34) also occurred significantly. Reports of Damage occupied the highest percentage among all the codes and among damage reports, environmental damage were the highest category. In the immediate aftermath of the disaster, there were significant a number of Request tweets. Some of the tweets were specific in asking for material support, but a larger percentage of tweets were just asking for help without being specific.

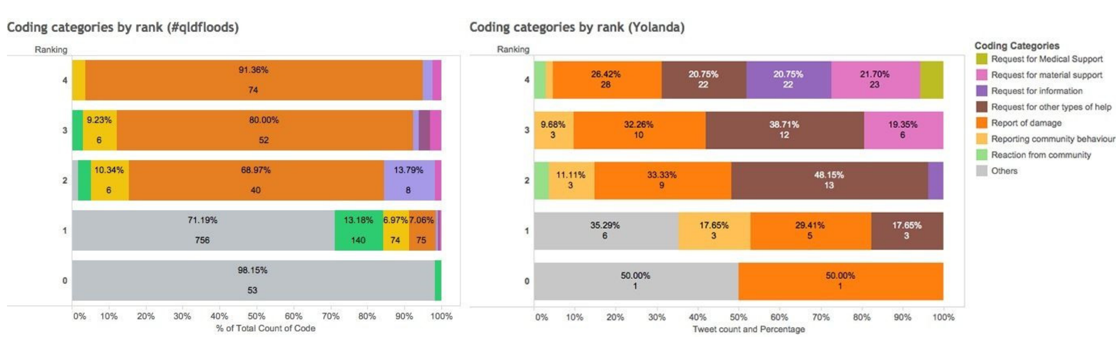


Figure 34: Comparison of distribution of tweets in their coding categories by rank

Relevance and priority A tweet can be **relevant** if it has any of these three themes: **Request, Report and Reaction**. However, it may not be of high priority.

Priority is determined based on **Urgency** and **Specificity**. Urgency can be identified based on keywords related to time and action. Specificity is determined based on extracted metadata such as location or image links. Although urgency can be difficult to determine due to word sense disambiguation, determining specificity is easier with the existence of location names or image. From the manual analysis it was found that more than 75% of the time, location and image indicates that the tweet is likely to be disaster relevant (Figure 35). It is important to note that in Figure 35, while the Yolanda statistics show little variation across the ranks, the Yolanda tweets were already categorised by the MicroMappers as containing disaster relevant information.

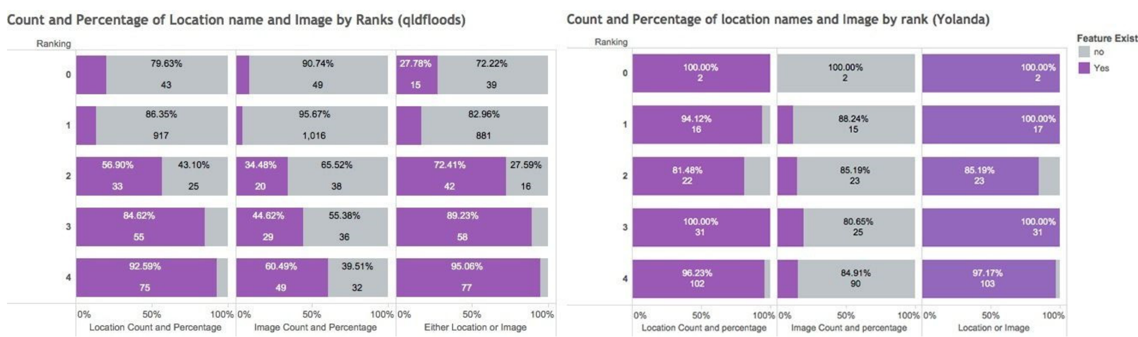


Figure 35: Comparison of image and location in tweets by rank

Keywords Words in the category of Request for Help / Need were similar in both disasters. Most of the words were related to “please”, “help”, “need” and they can be seen across all the categories. Although urgent words varied from dataset to dataset, there was a pattern in the words that was related to the disaster. For example, words related to flood were “now”, “near” and “rising” depicting water level, and words related to typhoon, “flying” and “falling” describing the effects of wind.

Categories	Thematic analysis	Keywords that appeared in both datasets
Request for material support (RF, RS)	Food and water, electricity, lights and candles, animals (dog, cat, horse), cell phone signal, relief not reaching	Animals, badly, bodies, candles, damaged, dead, dire, electricity, flashlight, food, goods, isolated, relief, rescue, signal, seeking
Request for medical assistance (RM)	Unavailability of medicine and injury related words such as getting hit by debris	Medicines, hurt, injured
Request for information (RP, RA, RI)	Family members, friend, relatives, unable to contact	Boyfriend, colleague, contact, families, family, father, find, husband, mum, old, power, situation, son, brother, mother, father, friend
Request for other types of help (RH)	Asking for help without being specific. Types of help often includes material support or request for information	Asking, dog, dire, evacuate, horse
Report of damage (DP, DH, DE, DC, DI)	Words and activity related to disaster. If it is flood, words such as rising water. If cyclone, building parts flying off. Building materials (roof, foundation), vegetation that can fall and cause destruction such as tree trunks. Road status.	Basement, blackout, bldg, block, bridge, brim, cables, casualties, corner, communication, damaged, debris, destroyed, detach, disconnects, door, down, electricity, failed, fallen, ferry, filling, flash, floating, flood, getting, height, hour, house, indistinguishable, impassable, knocks, leaning, lines, midday, near, number, outage, roof, storm, strong, street, surging, swallowed, terminal, trees, winds
Reporting community behaviour (CB, CC)	Donation, looting, evacuation - words that represent community situation as well as mood.	Creeping, donate, families, forced, helpless, homes, looting, lost, morgues, municipalities, near, polluted, power, submerged, temporary, washes, water, wrong
Reaction from community (RE, RC)	Some users tweet providing advice while some users point out if the relief efforts has been successful	Helping, asking, donation, received, send, volunteer, yet
Others (OM, OS, OG, ON, OR)	Spiritual messages, greetings, wish, asking to buy things, pornographic	According, amazing, business, buy, comparisons, ideological, God, Good, heart, hell, heroes, jobs, lord, love, mercy, miracle, pray, prayer, price, psalm, purchase, report, sexy, striking

Table 12: Summary of common and specific keywords in #qldfloods and Yolanda dataset

High importance words were usually found in the long tail distribution. Often these words were not the top keywords. Table 12 provides a summary of the types of word that appear frequently. A full list of keywords is available in Appendix E. In terms of part of speech, there was no definite pattern that was identified from the analysis. Therefore, even though it was deemed as relevant by other researchers, this is not used for the automated analysis of this research.

Adaptive system As Twitter becomes a mature system with increasing usage, the effect of complex adaptive system processes were visible in the later dataset (Yolanda). A lot of users tried to reach prominent Twitter users at the same time with the hope that they would promote the tweets to their followers to increase visibility among the people. More people tried to use hashtags to amplify names of places in the Yolanda dataset compared to the #qldfloods dataset.

4.5.1 Rule based filtering

Based on the findings of the qualitative analysis, the following filtering rules can be suggested for an incoming tweet:

> **1. Check for Retweet:** If the tweet is a retweet it should be eliminated. It is better to go to the source and eliminate any other tweet that refers to that tweet.
>
> **2. Look for an image:** As it was found in this chapter, a significant percentage of Reports of Damage included images. A lot of community reports also had an image in them. Therefore, if it has image, it has higher chance to be a relevant tweet for emergency services.
>
> **3. Find if it has specific name of location:** Similar to image, if the tweet has a specific location name instead of generic, it has higher chance to be a relevant tweet for emergency services.

4. Having desirable (Request, Report, Reaction) keyword: If it contains any keyword that is in the desirable keyword list, (under request, report or reaction) it is potentially relevant.

5. Not having undesirable keyword: If a tweet includes keywords such as God, then it is potentially not relevant for emergency services.

4.5.2 Limitations of the study

There were several limitations to the manual analysis phase. The primary limitation is that the findings are based on a small sample of a selected hashtag dataset. Even though a hashtag dataset is an acceptable research sample, identifying the right hashtag is often a challenging task. In addition, manual evaluation of the #qldfloods was conducted by a single coder. Although research has often used a single coder for their first pass in creating coding schema, having only one person's point of view may not be sufficient. The dataset evaluated from Yolanda dataset was also a very small percentage of the whole dataset. However as the objective of this phase was to identify the features for automated analysis phase, it does not pose a huge limitation. The next automated analysis phase attempts to address these limitations by automating the findings from qualitative phase to the larger dataset.

Chapter 5: Automated Analysis

The outcomes from Chapter Four (manual analysis phase) were used as a foundation for the design of the analysis described in Chapter Five (automatic analysis phase). This second phase of the research addresses the second sub-research question, how can relevant information for emergency services be filtered automatically. In the manual analysis phase, the question of **what is relevant for emergency services** was addressed and four features were identified that can determine if the tweet in question is relevant for emergency services after a natural disaster. These four features are, **a) location, b) image c) having desirable keywords (keywords that fall under Report, Request and Reaction categories) d) Not having undesirable keywords (keywords that fall under spam or personal narrative).**

This chapter describes the process taken to develop automated detection algorithms to find these four features in any given tweet. The process involved creating a set of tools that used several methods discussed in Chapter Three (Methodology) to automatically identify if the features exist in a tweet.

After the algorithm was developed, it was tested on the #qldfloods and Yolanda datasets, which had already been coded manually by the researcher (for #qldfloods) or the MicroMappers (for Yolanda). Having the tweets already coded in their groups allowed the researcher to compare the output of the algorithms with the manual coding, and to test whether the algorithm reliably identified the tweets which the coders had identified as relevant for emergency services. The flow of these various tests can be seen in Figure 36.

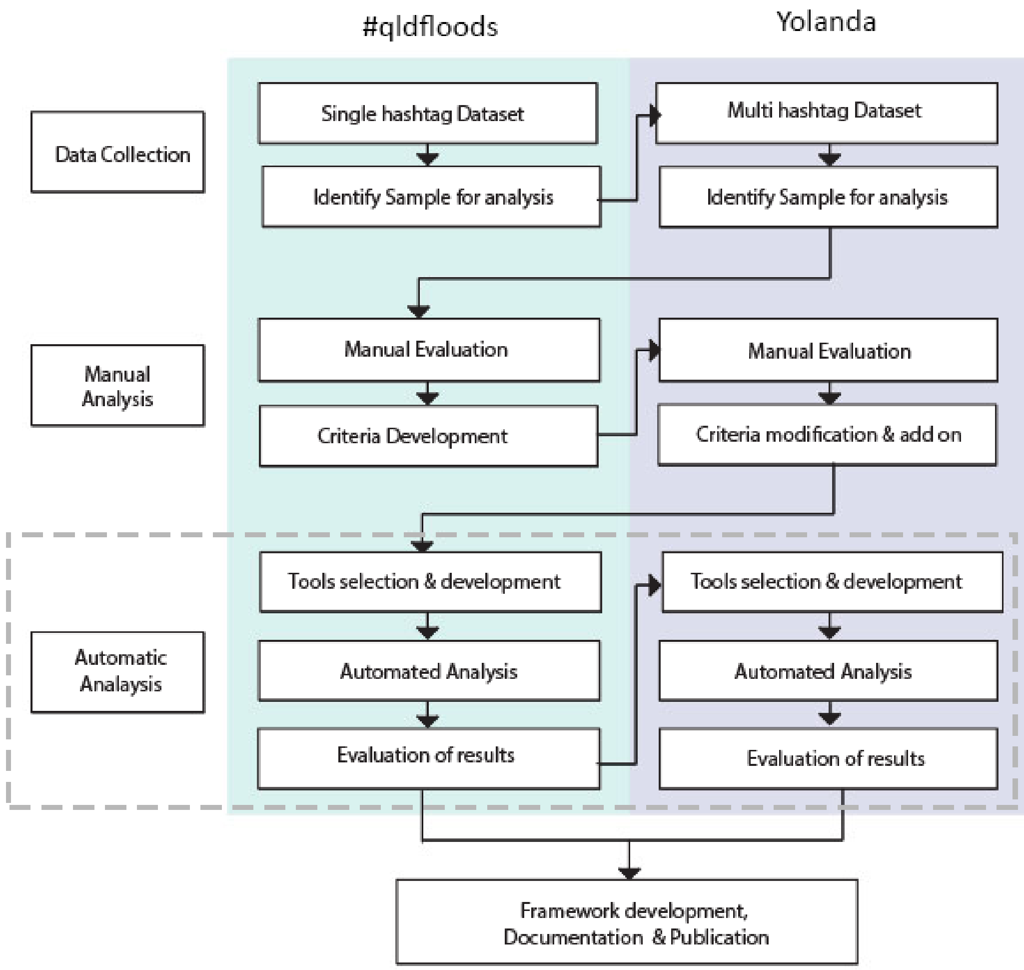


Figure 36: Research design flowchart – automated analysis (phase two)

5.1 Sample Size for Analysis

Although for an automatic analysis there are usually no limitation on the data size, only the 1,320 tweets from the #qldfloods dataset and 22,084 tweets from the Yolanda dataset was used for the automatic analysis**.** The reason for the selection is described in this section.

Dataset from #qldfloods In the original #qldfloods dataset there were 49,748 tweets collected using the #qldfloods hashtag. However, not all the tweets were coded and therefore it would not be possible to determine if the output from the algorithm was successfully identifying tweets that were relevant for emergency services or they were finding tweets at random. Therefore, the same **1,320 tweets from #qldfloods dataset** that was used in manual analysis phase was selected for automatic analysis. Although this is a small dataset for the automatic analysis, as they were already coded they could be used to determine the performance of the algorithm. It should be noted that this dataset already excludes retweets.

Dataset from Yolanda Similarly, the initial Yolanda dataset had more than 230,000 tweets. By selecting tweets that were written during the first 24 hours it was reduced to 52,548 tweets. Out of that, **22,084 tweets** were selected for the automated analysis. This is because to compare the output from the algorithm any tweet from the database should be clearly marked as relevant or irrelevant for emergency services. In order to prevent any confusion, tweets that had at least 50% agreement among MicroMappers were used in this phase. This resulted in 26,068 tweets, which was filtered again to remove any tweets that started with RT. This resulted in total of 22,084 tweets.

Once the sample sizes were determined, the tweets were evaluated using the algorithm to identify if they contained the four features. The next section describes the development of the algorithm, which is followed by the results from the analysis of each dataset.

5.2 Mapping Features and Methods

This section describes the process of developing the tool set that was used to test the four features. For each feature identification new scripts were developed which were built on established frameworks of computer science and information retrieval. Related scripts and setup methods are listed in Appendix D.

5.2.1 Image and URL distribution

To identify image and URL distribution, a combination of regular expression in Python programming language and URL Resolve framework was used. For each tweet, the script looks for any URL in the tweet by looking for “http” or “https” and then once it finds any URL, it then uses the URL Resolve library to convert any short URL to the full URL.

Another script then was executed to find if a tweet has links from any of the top 25 popular image sharing websites. The list of top 25 image sharing websites was gathered from Wikipedia, which is often updated by contributors. Since popularity of an image sharing website may change rapidly, identifying information from Wikipedia can ensure it covers the currently popular image sharing websites.

5.2.2 Named entity extraction

For the purpose of named entity extraction, there are several competing named entity analysis and natural language processing frameworks available. Among them, three of the most notable frameworks are Stanford Named Entity recognition (Finkel, Grenager, & Manning, 2005) (with updated 2014 classifier), University of Washington Twitter NLP Tools (Ritter, Clark, & Etzioni, 2011) and Carnegie Mellon Ark-Tweet-NLP (Owoputi et al., 2012). As Stanford NER is the most popular framework, it was selected to use for this study. A python script was written that reads the tweets from the database, splits the words of the tweets, removes any symbols such as @ or # and then calls the Stanford NER tagger to identify if there are any named entities available. According to the tagger, a named entity can be of any of the seven classes: Time, Location, Organisation, Person, Money, Percentage, and Date.

5.2.3 Keywords

The experiments using keywords built on the list of desirable (e.g., Report of Damage) and undesirable (e.g., Spam, personal narrative) keywords developed in previous chapter (Table 12). However, instead of only looking for the exact word, each of the words were reduced to their base morphological form to match a greater number of words. For example, instead of only looking for a word “blocked” which may have referred to the inability to access a certain road, its root form “block” was used. Words such as “blocking”, “block” are therefore also covered under the root term “block”.

Base morphological forms through stemming The most common process of identifying and correcting words in their base morphological form is via stemming (Han, Cook, & Baldwin, 2013). By converting words in their root form, stemming reduces number of times a word needs to be checked for variation. Stemming of words has been practised in natural language processing for many years (Manning & Schütze, 1999). For the purpose of this project Porter Stemming (Porter, 2001) was used as it is the most versatile stemming available. The stemming process was applied to each of the words in the tweets as well as on the keywords in the list described next.

Desirable keywords list The list of desirable keywords were built on the list that was created in Chapter Four. Although the list included categories from Report, Request and Reaction, for the purpose of automatic analysis words from the Report of Damage category were tested (Table 13). The reason for picking only this sub category was that it was the most prominent category in the #qldfloods dataset and one of the most prominent categories in the Yolanda dataset. Although other categories such as Request for Information could have been selected there was not have sufficient data to test from #qldfloods. Therefore, in order to maintain consistency and academic rigour the Report of Damage category was selected.

Category	Words
Report of damage	Basement, blackout, bldg, block, bridge, brim, cables, casualties, corner, communication, damaged, debris, destroyed, detach, disconnects, door, down, electricity, failed, fallen, ferry, filling, flash, floating, flood, getting, height, hour, house, indistinguishable, impassable, knocks, leaning, lines, midday, near, number, outage, roof, storm, strong, street, surging, swallowed, terminal, trees, winds

Table 13: Desirable Keywords listed under Report of Damage category that was used for testing

Undesirable keywords list Similarly to the desirable keywords list, keywords from the Others category contained words from the undesirable keyword list. These included keywords related to personal narrative, spam, spiritual messages, news and reports; categories that were identified as not relevant for emergency services. These are detailed in Table 14, which draws on the Table 12 developed in Chapter Four.

Category	Words
Others	According, amazing, business, buy, comparisons, ideological, God, Good, heart, hell, heroes, jobs, lord, love, mercy, miracle, pray, prayer, price, psalm, purchase, report, sexy, striking

Table 14: Undesirable keywords listed under other categories that was used for testing

Matching process As the objective of this step was to automatically identify if a tweet contains desirable or undesirable keywords in order to automatically identify tweets relevant for emergency services, the first step was to take each word from the lists above (Table 13 for desirable keywords and Table 14 for undesirable keywords), stem it and store in a temporary location. After that the script loops through the database of tweets and for each word of a tweet the script converts them into their base form and compares them with the words that are stored in the temporary location. If the words were a match, that tweet was marked as a match. After the scripts looped through the samples, the output was exported to a file for further analysis. The output of this matching process for #qldfloods and Yolanda dataset are explained and analysed in more detail later in this chapter.

5.3 Phase Two Part One: #qldfloods dataset

This section explains the findings from running the tool set on the #qldfloods dataset for the four selected features. As this dataset was already pre filtered for retweets, retweet elimination is not included in the discussion of results. Findings from remaining features and how they compare against the coding categories are described below.

5.3.1 Image distribution

The findings from the manual analysis phase placed high importance on the existence of an image in the tweet. Therefore the objective of image identification was to find out which categories of tweets had more images in them. As discussed earlier, this was done by first finding the URLs in the tweet and then by identifying which of those URLs had images that were relevant. As can be seen from Figure 37, a large number of tweets did not contain any URLs.

For the purpose of analysing this dataset, websites such as twitpic, yfrog, imgur were marked as third party Twitter images as they were used to link to photos in tweets. As is demonstrated in Figure 37, one third of Report of Damage tweets had third party image URLs in them.

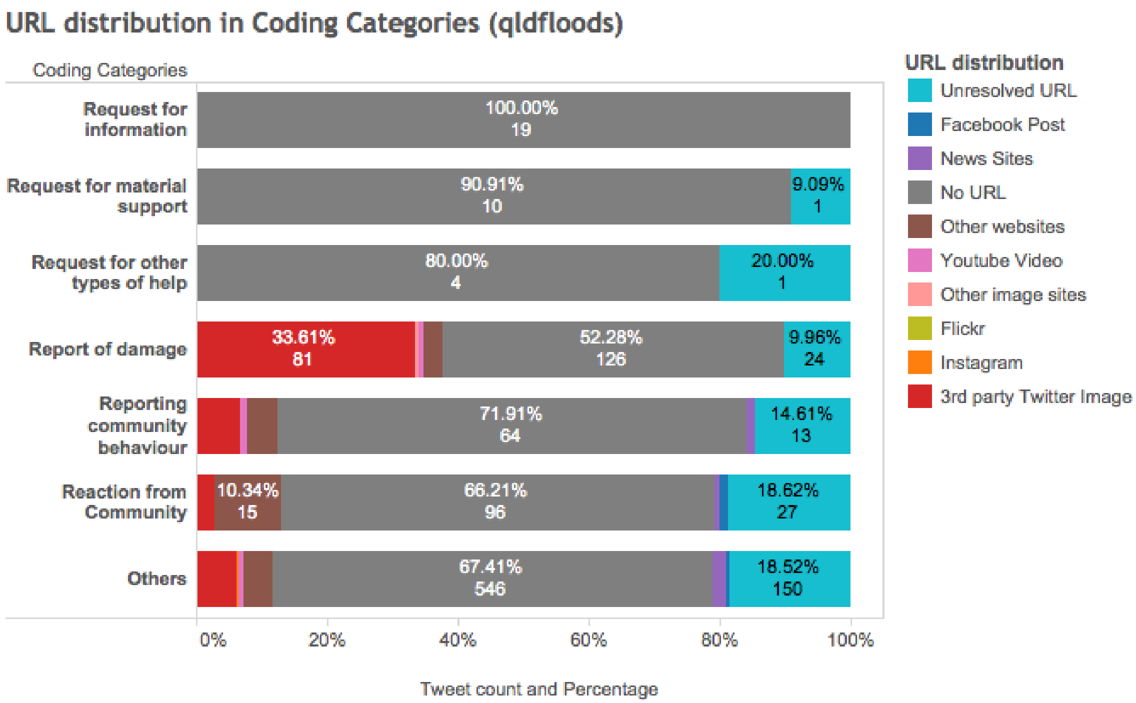


Figure 37: Distribution of coding categories in image based tweets

One category that stands out is the category of unresolved URLs (shortened URLs that did not convert to their full form). There are two main reasons for this. The first is that when people retweeted sometimes the links were truncated in a way that it missed certain portion of the URL and therefore became unresolvable. Second reason is this dataset is an old dataset that contained links that no longer existed. Therefore even though a number of additional images were identified in the qualitative phase that belonged to the report of damage and request categories, either the links or the websites were not available any more.

Other notable URLs such as Flickr and Instagram were grouped as one. Although these are extremely popular websites the popularity of a website often changes very quickly. Therefore instead of grouping based on a specific website those websites that were currently popular were grouped into one. This pattern of image sharing can assist emergency services to look for currently popular image sharing websites instead of looking for websites that may no longer be popular.

Overall it can be seen that the findings from analysis of #qldfloods dataset of the importance of images was confirmed through the automated tool. Among the categories it can be seen that Report of Damage had the highest percentage of image based tweets.

5.3.2 Named entity distribution

In manual analysis phase it was identified that if a tweet contained mention of a location, the tweet is likely to be relevant for emergency services. Therefore by using the Stanford Named Entity recognition framework this section automatically analysed each of the tweets from the #qldfloods dataset to find out what percentage of tweets in each group contains mention of a location.

Before proceeding to examine the output, it is necessary to briefly explain named entity extraction. Most of the named entity extraction tools look for specific information. Depending on the classifier it uses, the tool looks for mentions of specific information such as location, organisation, name of person. The reason the initial experiment was not focused only on location was to test the general distribution of named entities in the dataset.

As can be seen in Figure 38, in most of tweets named entities were either not present or were not automatically identified. However, Report of Damage had the highest number of locations followed by request for information and the Other category. This preliminary result aligns with the findings from the manual analysis about the importance of location in tweets.

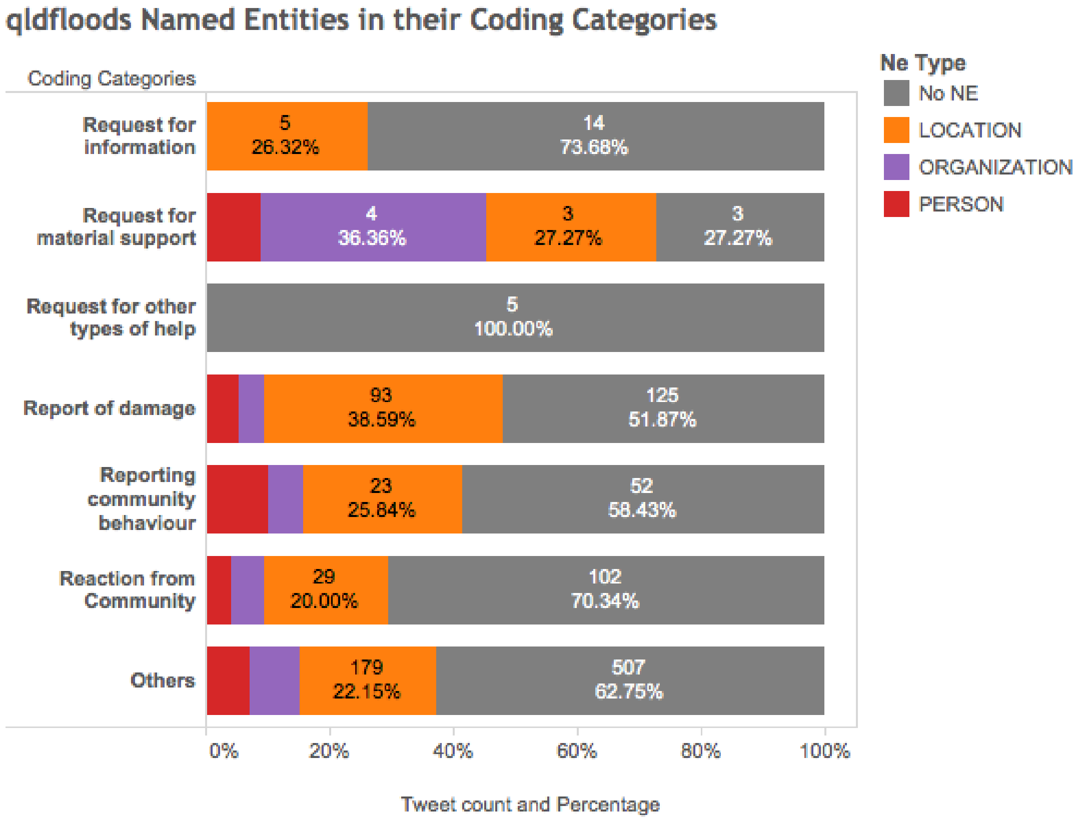


Figure 38: Distribution of types of named entity in their coding categories

However, in the manual analysis it was also identified that mention of specific locations were more relevant to emergency services than generic locations. Therefore the type of location these tweets included was investigated further. In order to see the distribution of location names, they were divided into two parts. If the location name was large area such as Country (Australia), State (Queensland), City (Brisbane, Sydney) it was grouped as a generic location. If the tweet had a specific regional location it was grouped under Specific Location. If the tweet did not have any location named entity, it was grouped as No Location.

As it can be seen from Figure 38, the Other category had more generic locations such as “Australia”, “Queensland”, “Brisbane”, compared to the report of damage category which had more specific locations such as “Margaret Street”, “Bulimba” (a suburb in Brisbane). This is similar to the findings in manual analysis phase that identified that having a specific location is a good indicator of a relevant tweet.

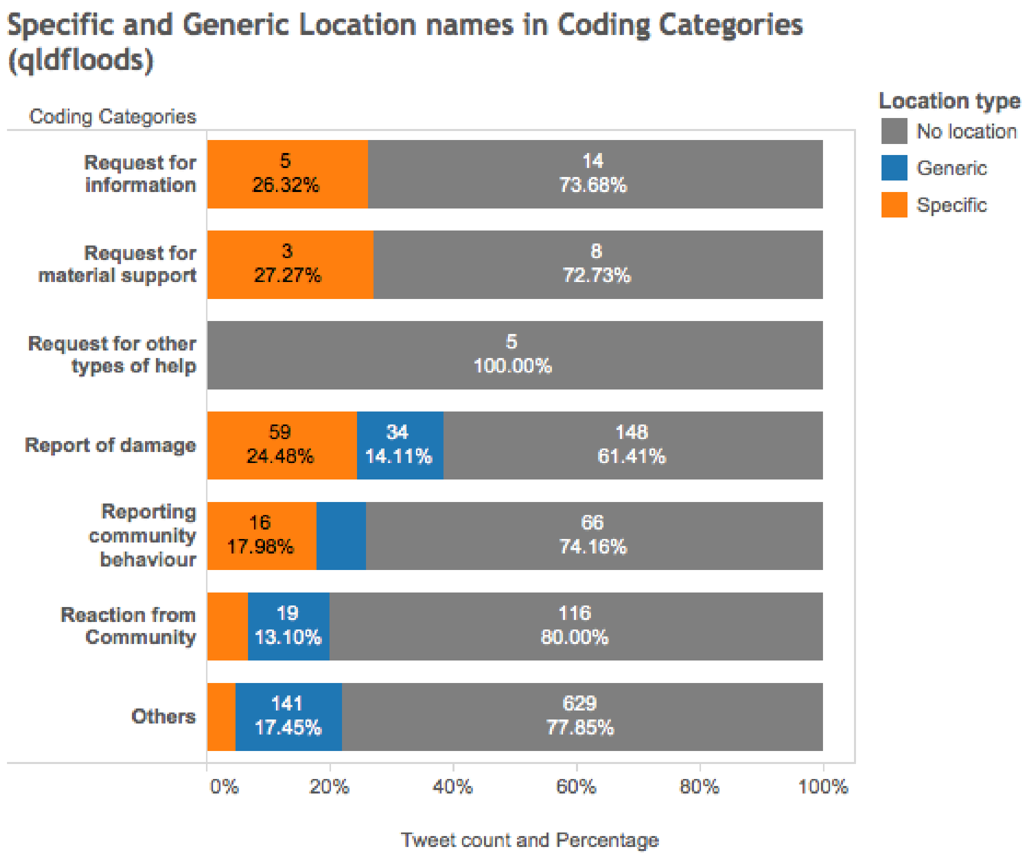


Figure 39: Distribution of specific and country wide location in coding categories

By analysing further it can be seen that regional locations indeed identified tweets that are likely to be relevant to emergency services. For example, tweets such as "Corner of Horizon Drive and Dewsbery Street Middle Park @ Midday. #bnefloods #qldfloods http://twitpic.com/3p8pnu" or "Moggill Road Chapel Hill a good 500m from Brisbane river (taken 2hrs ago): http://goo.gl/photos/PtG1oNOYG7 #qldfloods #bnefloods" contains relevant information for emergency services.

However the tool did not always automatically identified something correctly. For example, the tool identified the word "Seinfeld" as a regional location from the tweet "@MsDovic @therealzooeyd @amandapalmer @DannyDeVito and Jason Alexander from Seinfeld - don't have his acc sorry #qldfloods", which was in the others category. Similarly, "It must be very humid in Brisbane Karl keeps wiping his forehead mid interview .... #Qldfloods" was grouped under Specific Location because it identified "Karl" as a name of a location.

Sometimes the tool identified the regional location accurately, but the tweet itself was not relevant for emergency services. For example, in the Tweet “Federal Member Capricornia Kirsten Livermore says a study into Yeppen crossing into #Rockhampton has been underway prior to the #qldfloods”, “Rockhampton” was identified as a specific regional location, but the tweet itself was not relevant for emergency services.

Therefore it can be suggested that named entity recognition is indeed a marker to identify disaster relevant tweets automatically. However, it is not free of errors and therefore not sufficient to determine if a tweet is disaster related or not. In addition, the question of whether it only worked for names that are English-based needs to be tested. Therefore in the next stage of the analysis the same tool was applied to the Yolanda data set to see if it could identify the names of places in a non-English location, the Philippines.

5.3.3 Keywords distribution

Keywords are integral of any form of information retrieval activity (Brin & Page, 1998; Matsuo & Ishizuka, 2004). Although Twitter only has 140 characters, and based on the discussions so far, image and named entities have a strong importance, keywords still play a very important role in identifying the context of a tweet (Mathioudakis & Koudas, 2010).

In addition, it can also be argued that since the amount of words that can be used in twitter is minimal, existence of multiple disaster related keywords in a tweet is likely to indicate that this tweet is potentially relevant for emergency services (Purohit et al., 2014; Roy Chowdhury, Imran, Asghar, Amer-Yahia, & Castillo, 2013). Similarly, if the tweet contains more undesirable words, it is likely to be an irrelevant tweet for emergency services. To test this assumption, all keywords listed in Table 13 and Table 14 were tested on the #qldfloods dataset. This section describes the findings of this test.

Desirable keyword distribution Figure 40 shows the problem identified by researchers with regards to word sense disambiguation (Banerjee & Pedersen, 2002). Although these were the keywords that were identified as relevant for emergency services while evaluating the tweets manually, and they have appeared in high percentage in the Report of Damage category, they also appeared in high numbers in the Others category.

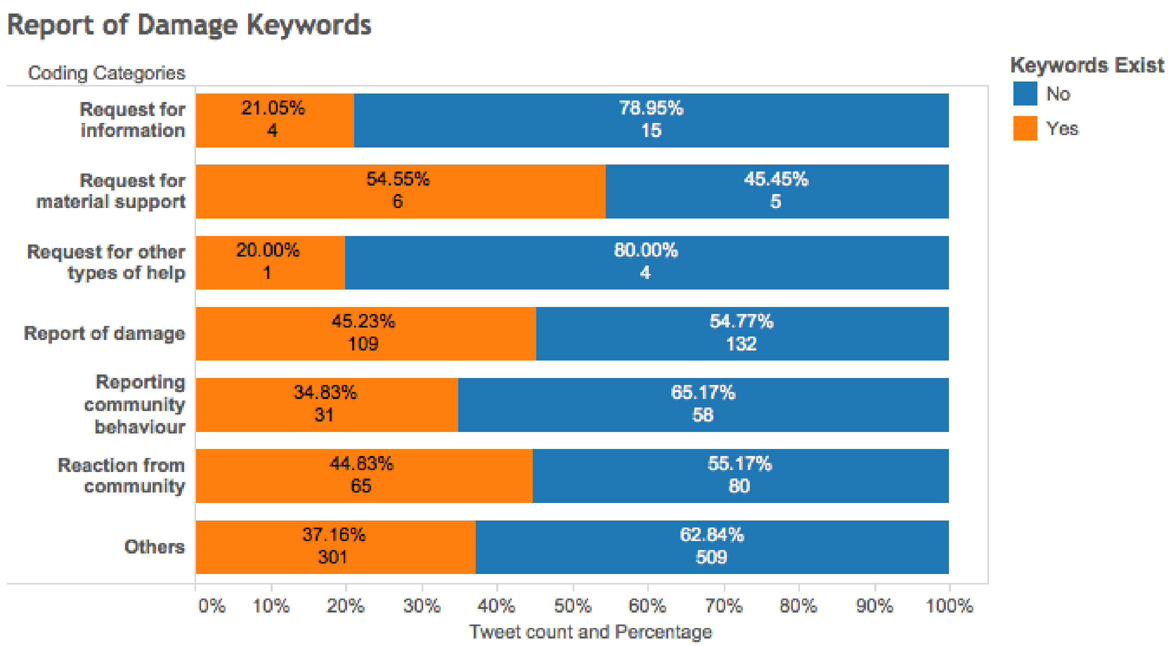


Figure 40: Distribution of coding categories in Report of Damage and Request

For example, the word "destroyed" is a disaster specific and relevant for emergency services word because it can be in a tweet about a particular building, public infrastructure or property getting destroyed. However, this tweet "Lord Mayor Campbell Newman: CityCat ferries and terminals destroyed on the Brisbane River. #qldfloods #thebigwet" also has the word destroyed and would be marked as relevant if the relevancy is determined by the word "destroyed", even though it is not relevant for emergency services.

Even for something that is even more specific, such as the word "mum" which was in the request category, the tweets can be in both the relevant as well as irrelevant group. For example, "Can anyone on #BribieIsland pls confirm conditions? Cannot ctc my 96 year old mum at Bongaree. Pls DM me #qldfloods" is clearly an important and relevant tweet for emergency services. However, "Just spoke to Mum she's emptying the fridge before the power turns off at 10am then heading to higher ground at my sister's home #qldfloods" is more of a personal narrative than a tweet of disaster relevance.

Common keywords were found to be even more problematic. For example, there were tweets that mentioned floodwater coming towards the house and were categorised as a Change of Situation tweet and resulted in the inclusion of the word "coming" in the keyword list. However this resulted in identification of irrelevant tweets such as "#qldfloods twitter stream is almost unreadable - simply too many tweets coming through", which although mentions the flood, is about the flood of information and not the flood of water.

The findings indicate that what was thought as desirable keyword during manual analysis was found to be not desirable in the automatic analysis. Although desirable keywords that fall under the Report, Request and Reaction remain a necessary feature, they need to be constantly evaluated to ensure automated analysis does not identify tweets that are irrelevant. This can be improved by integrating results from undesirable keywords, which is explained next.

Undesirable keyword distribution Results from the findings detailed in Figure 39 show that undesirable keywords can potentially be more useful to identify if a tweet is irrelevant for emergency services. As can be seen from Figure 39, undesirable keywords had a higher percentage in the Others category which has tweets marked as personal narrative or spam, compared to the categories that has been marked as relevant for emergency services. Although Reaction from Community had a higher percentage than Others category, Reaction often contains personal narratives that share many of the same keywords with Others. Apart from that, undesirable keywords were found in higher percentages in the Others category.

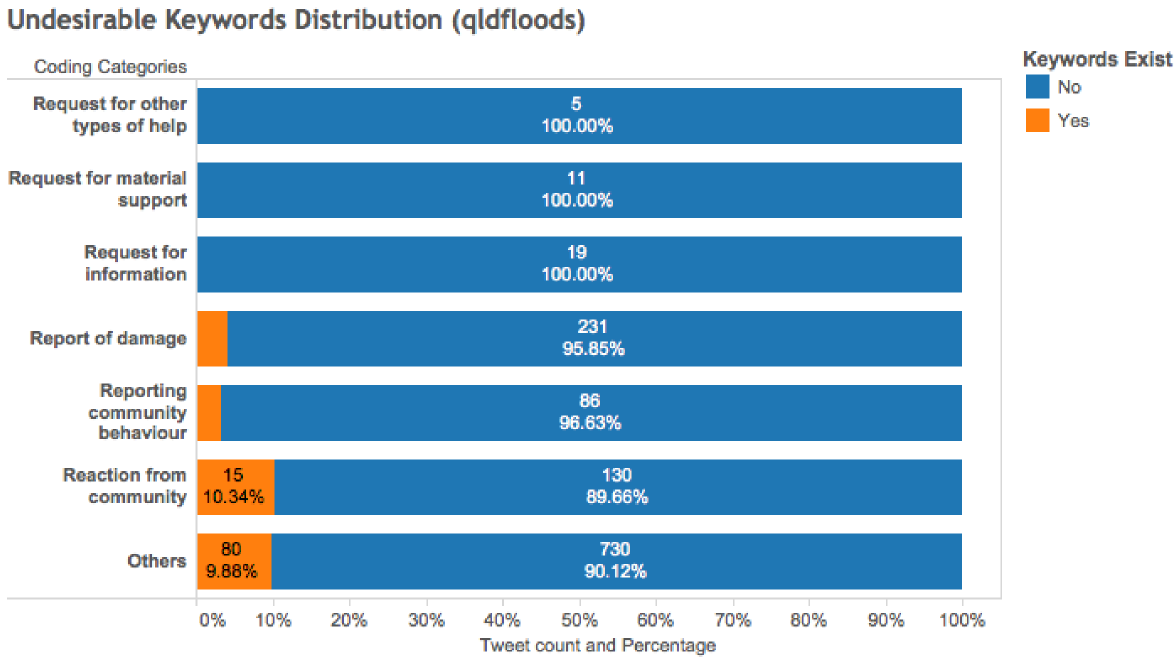


Figure 41: Distribution of coding categories for undesirable keywords

One exception was "Moggill Road Chapel Hill a good 500m from Brisbane river (taken 2hrs ago): http://goo.gl/photos/PtG1oNOYG7 #qldfloods #bnefloods" tweet which is relevant for emergency services and eliminating the tweet based on the word "good" would eliminate a disaster relevant tweet. Therefore, it can be suggested that either words such as "good" should not be listed (which was included as a part of greeting word - "good morning") or that undesirable keywords can not be used a sole evaluator either.

Based on the result can be suggested that keywords alone, especially the undesirable keywords alone would not be able to identify a disaster relevant tweets on their own. Ultimately they can be used to generate a result set that is a subset of the total collection of tweets. They can also be used to assign a certain score and increase the score if desirable keywords exist and undesirable keywords do not exist. An additional method of using Wikipedia and Wordnet synonym to expand keywords is included in Appendix F. However, using keywords alone would be insufficient to determine if a tweet is relevant for emergency services.

5.3.4 Summary of findings

This section summarises the findings from using various tools used on the #qldfloods dataset to find if the features that were selected as markers of relevance in the qualitative phase one can identify if a tweet is relevant for emergency services automatically.

This analysis showed that image and URL detection the tools can successfully identify the existence of images whether it is linked or embedded. In addition, by scraping the names of top image sharing websites from Wikipedia, it can identify if a particular URL is an image sharing website or something else. For named entity as well, the Stanford Named Entity Recognition tool can successfully identify specific local areas. By providing an additional list of wider area location names that need to be excluded, it can identify tweets that are likely to be relevant for emergency services automatically.

When it comes to keyword the success of the tools are rather limited. Although keywords from the irrelevant keyword list are more successful in determining tweets that are likely to be not relevant for emergency services, keywords from the relevant keyword list were not successful in identifying tweets relevant for emergency services alone.

Overall, the tools and frameworks can successfully identify the features to a level of success. However none of the tools were found to be able to determine on its own if a tweet is relevant or not. Rather it appears that a combination of the tools is likely to create a better identification option than a single tool. However, before concluding that a combination feature is potentially better, it needs to be tested on a bigger dataset. Therefore, in the next section the same set of tools were used on the Yolanda dataset.

5.4 Phase Two Part Two: Yolanda dataset

From the discussions of the findings from the #qldfloods dataset it can be seen that automated tools can successfully identify the features Image, Named Entity and Desirable and Undesirable keywords from tweets. However to test if the tool set successfully identifies these features from a much larger dataset, the set of tools and frameworks were applied to the Yolanda dataset. The findings are described in the following sections.

5.4.1 Image distribution

Distribution of the image sharing websites in Yolanda tweets (Figure 43) suggests that tweets in the Damage to Infrastructure category are substantially more likely to contain images, meaning that tweets with images are likely to be relevant to emergency services. By grouping all other websites in the same group and separating only Twitter images and Instagram URLs it can be seen from Figure 43 that Damage to Infrastructure has the highest percentage of images among all categories.

However from Figure 43 it can also be seen that the Not Relevant category had a large count of Twitter images as well. In terms of percentages most of the categories had a similar percentage of images. Therefore what images were shared was investigated further to understand if there was a certain distinction between relevant and irrelevant categories and if that could be automatically distinguished as well.

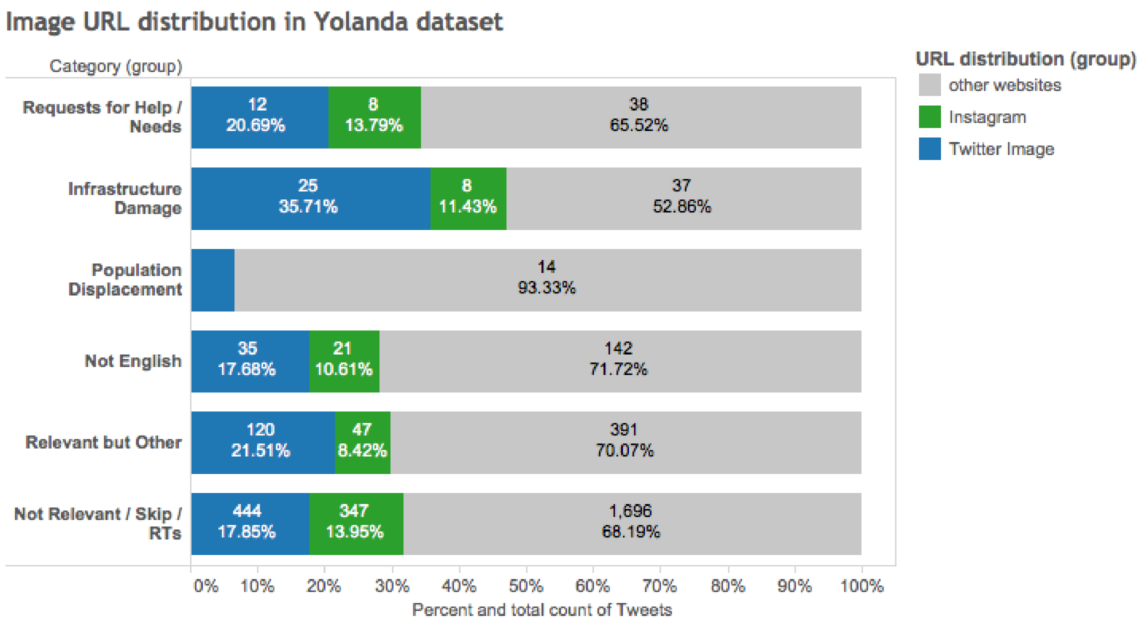


Figure 42: Distribution of coding categories in tweets with images

In depth observation Once the images are evaluated it becomes obvious why the image was marked as irrelevant or relevant. For example, in Figure 44 it can be seen that even though the tweets contained either the hashtag or keyword Philippines, they were clearly not relevant for emergency services.

Figure 43: Sample irrelevant tweets for emergency services that has photos

However, there were other images that were clearly relevant for emergency services. For example, Figure 45 shows some of the images that clearly indicate reports of damage. The interesting difference between these two groups of images that can be seen in Figure 44 and Figure 45 is that the relevant images also had specific names of places as well as keywords that were in the keyword list identified earlier. On the other hand, irrelevant images had neither a keyword potentially relevant for emergency services or a specific location.

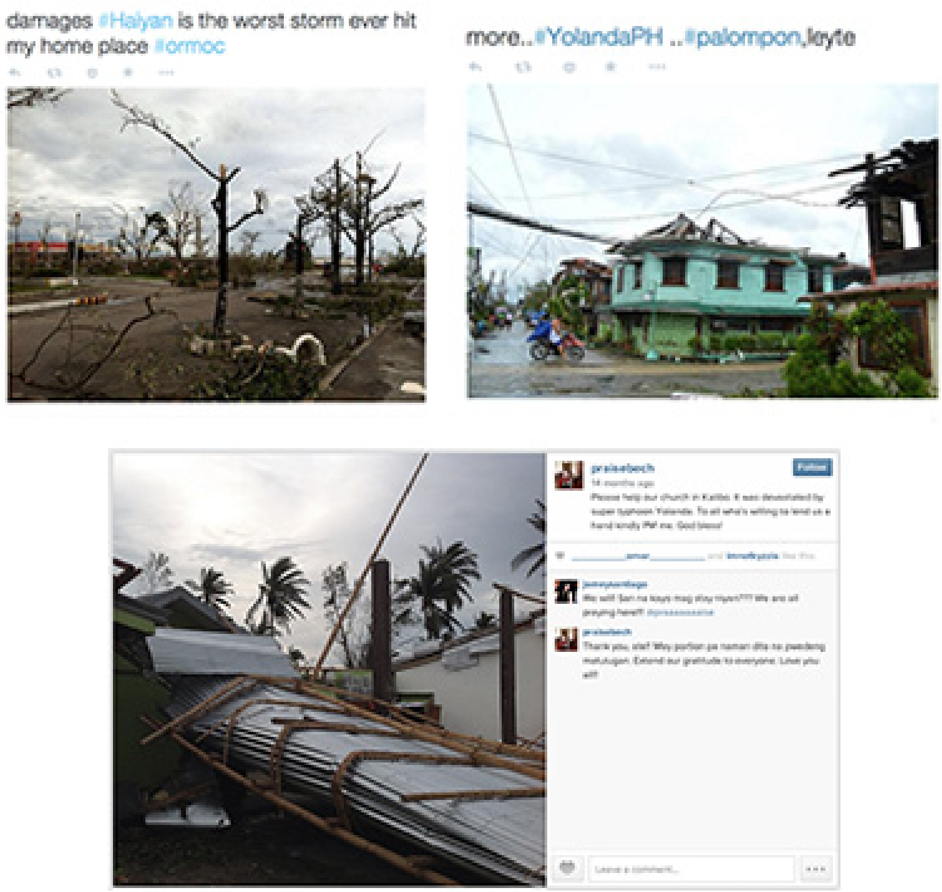


Figure 44: Sample tweets relevant for emergency services that has photos

Therefore, based on these findings it can be suggested that images alone are not a sufficient identifier of importance. Once an image is identified it needs further filtering to find those tweets that are relevant for emergency services. Instead, names of a place as well as keywords might be more appropriate for emergency services to identify disaster relevant tweets. Therefore these are tested in the next sections.

5.4.2 Named entity distribution

Once the Stanford Named Entity Recognition was executed on Yolanda dataset, it can be seen that location was dominant across all categories, except the Not

English category (Figure 46). Although the percentage of named locations is similar to #qldfloods, this dataset included other named entities, notably Person and Organisation. In addition, a notable difference with #qldfloods is that many tweets had more than one named entity. For example, it was common to see organisation or person in the same tweet with a location. However this was later identified as a mis-identification by the tool, as will be explained later in this section. However, as it was identified that the existence of a location is more likely to make a tweet disaster relevant this was investigated further.

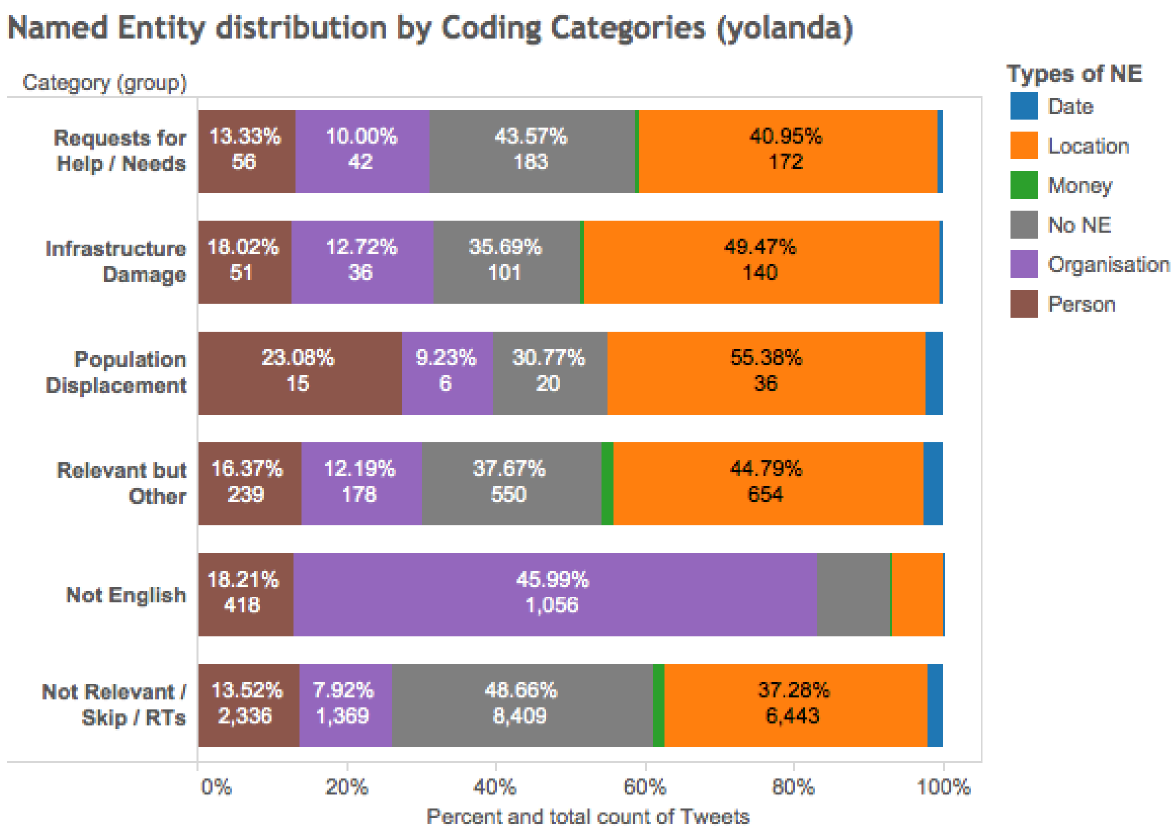


Figure 45: Distribution of categories in each named entities (Yolanda)

Filtering by generic names As it can be seen from the findings from the #qldfloods dataset, tweets that mention location and are relevant for emergency services are likely to include specific location names rather than generic names. Therefore tweets with locations were filtered with generic name filtering. For the purpose of this filtering, if the location was a large areas such as the Philippines, or neighbouring countries also impacted by the typhoon including Vietnam, Cambodia, Korea or any other countries, it was regarded as a generic name. If the named entity was not a location, it was grouped as No Location. For those that included a location but did not fit in the generic name, they were grouped as a Specific Location. Once this filtering was applied, the results changed drastically (Figure 47). Instead of having similar importance based on percentage of location names across all categories, categories that are relevant for emergency services are now more prominent due to the increased percentage of specific locations in them.

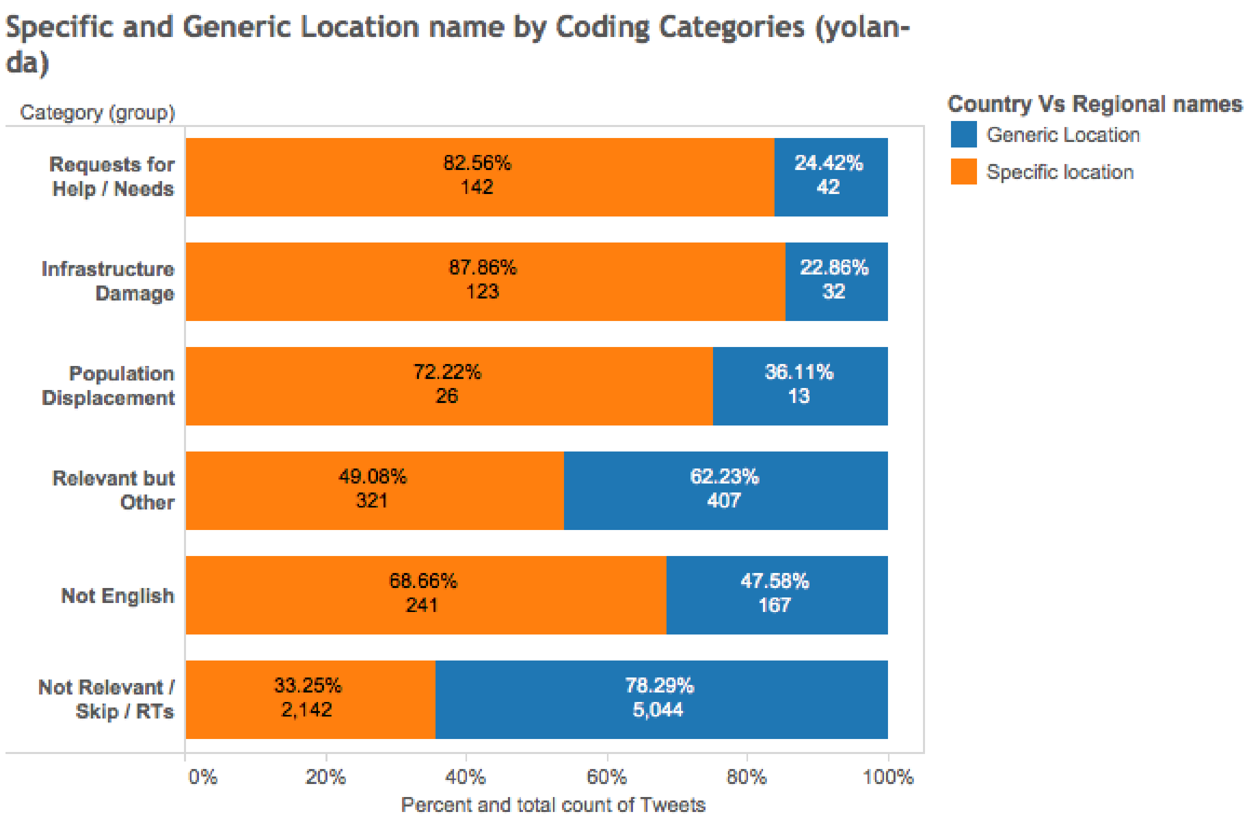


Figure 46: Distribution of generic and specific locations in tweets with location mention (Yolanda)

However, there was still a large number of tweets that were under the Not Relevant category but had a specific location in them. Although it was lower than other categories, in terms of total tweet count it was still significantly large. When these tweets are analysed it could be seen that although they contained specific location names they were not relevant for emergency services. For example, some of the tweets were, “Biliran and Tacloban, Leyte are close to me. I wish for their safety. #YolandaPH #Haiyan", "Glad to know na okay fam ko in negros but still ds doesn't stop me in praying 4 d safety of every1..? #YolandaPH #PrayForThePhilippines".

This provides an indication that, after the named entity level identification, tweets still needs to be filtered for other features such as keywords to identify if the tweet that had a specific location is indeed relevant for emergency services or another personal narrative that is not useful for emergency services.

Non English words was identified as organisation and person In addition to the location entity, additional observations could be made based on the analysis. A high number of tweets in the Yolanda dataset were a mix of English and Tagalog (the language of Philippines), resulting in words such as "Kagabi", "Grabe", "Lang", "Si", "papa" being identified as an Organisation. English words, "Metro", "Manila", "High", "School", "OCHA", "Flash", "Update", "NASA" were identified as Organisation as well. While NASA is indeed an organisation, Manila is a location and not an organisation.

It should be noted that, in terms of the names of locations there was not a significant difference in identification between English location names such as Margaret Street and non-English location names such as Tacloban. This suggests that named entity analyses might also work for non English tweets. However this was not investigated as it falls outside the scope of this dissertation.

Overall, findings from applying the named entity extraction tool to the Yolanda dataset confirm that named entity recognition is an important marker to identify disaster relevant tweets automatically. Similarly to the findings from the #qldfloods dataset, the results here also caution that named entity recognition does not work perfectly all the time and therefore relying only on this tool to identify disaster relevant tweets will not generate accurate results. It is therefore likely to be better suited as a part of a combined toolset, which is discussed in the following chapter.

5.4.3 Keywords distribution

As discussed earlier in this chapter with the #qldfloods dataset it was found that desirable keywords from Report, Reaction, Request categories are not only found in tweets that are relevant for emergency services but also in those categorised as irrelevant (e.g., spam, personal narratives). The objective of repeating the same test on the Yolanda dataset was to find out if the results were similar or if the findings from #qldfloods were specific to that dataset. The same two sets of keywords were used in this experiment, with one set that contained Report of Damage keywords and another set containing Others keywords. This section describes the findings of applying the tool on Yolanda dataset.

Desirable keyword distribution The findings of the desirable keywords distribution in the Yolanda dataset were quite different than the #qldfloods dataset. In #qldlfloods the distribution was almost equally distributed. However in the Yolanda dataset, there was a large percentage in the Damage of Infrastructure. The rest of the categories had similar percentages of desirable keywords, similar to #qldfloods.

However, as desirable keywords were present in the Not Relevant category of tweets, they were evaluated further. Based on a close reading it was found that although the tweets contained the keywords, the context was different. For example, the word "damage" was present in the Damage to Infrastructure and Not Relevant categories very differently. In the Damage to Infrastructure category there were tweets such as "Typhoon also caused heavy damage on the newly established hospital Health Centrum. #Capiz #YolandaPH #HelpCapiz http://t.co/MKHnuXJAmX". In the Not Relevant category, "damage" was found in tweets such as "Dont just share what you feel about the damage caused by Yolanda, MOVE and HELP. #YolandaPH" or "@PeterG_Weather I can't even begin to imagine what gusts of wind over 200 mph would feel like, let alone what damage they could do. #Haiyan". Although both tweets contain the word "damage", the context is completely different. This reflects what was found in part one of phase one.

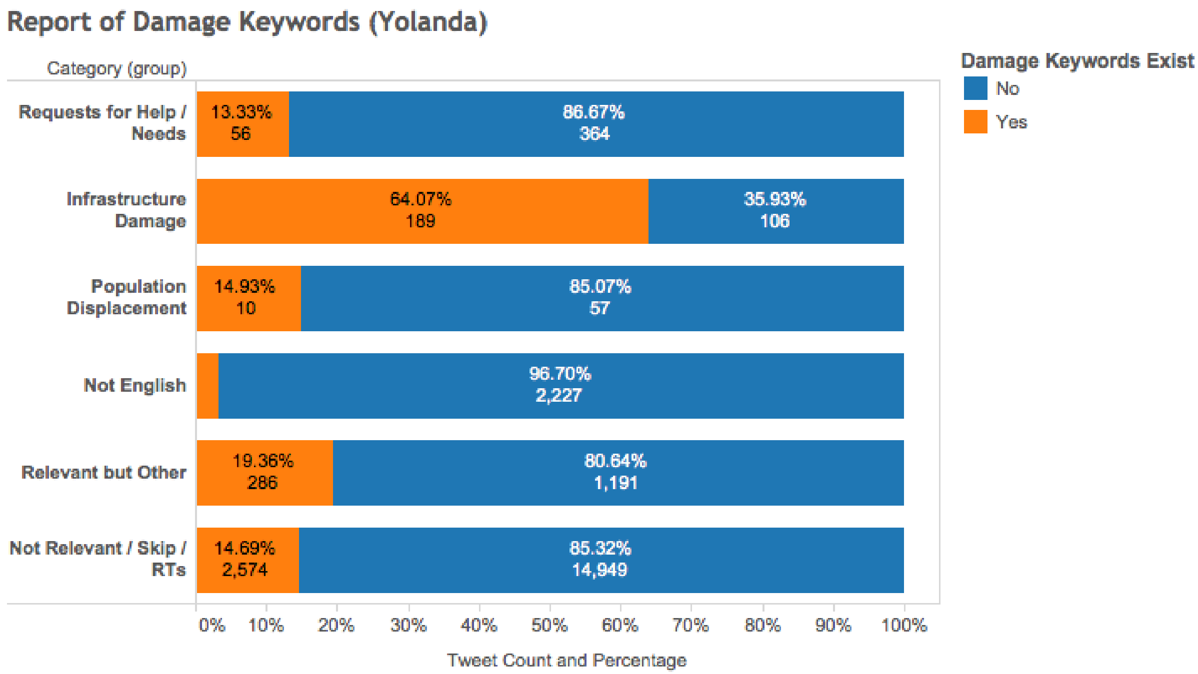


Figure 47: Presence of desirable keywords in their coding category (Yolanda)

The findings were similar for the Request category as well. Even for something very specific such as, "boyfriend", there were drastically different tweets. On one hand, the Request for Help / Needs category had "#rescueph my boyfriend is in Ormoc and we haven't been able to get in touch. He's in the Villa Hotel if anyone can help" and on the other hand not related category had "I WISH I'LL MEET ONE DIRECTION AND HARRY ATYLES WILL BE MY BOYFRIEND!! =D HELLO I'M KT DENISE. FROM PHILIPPINES!!! =D #wishogram". As these tweets were collected using hashtag #yolandaph, #rescueph and keyword Philippines among many other keywords and hashtags, the tracker collected tweets with various ranges of contexts.

Undesirable keyword distribution Similarly to the desirable keywords, the distribution of undesirable keywords was different from the #qldfloods distribution to the Yolanda dataset. As can be seen from Figure 48, although Not Relevant / Skip / RTs has the highest percentage of undesirable keywords, almost all other categories had a similar percentage of undesirable keywords as well.

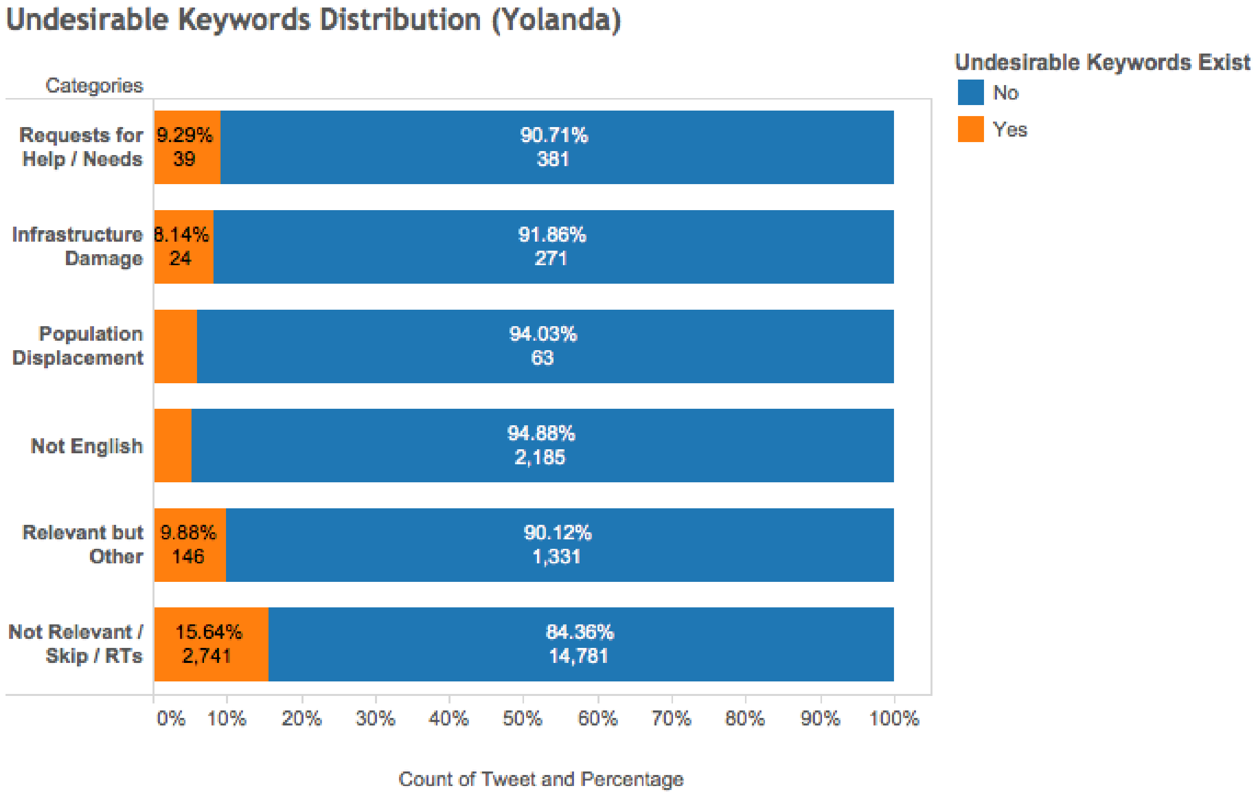


Figure 48: Presence of undesirable keywords in their coding category (Yolanda)

The findings here are different from #qldfloods because in #qldfloods it was found that the Others category, which included irrelevant tweets such as spam and personal narratives, had the highest percentage of undesirable keywords. However, by applying the same keywords list on Yolanda, a different result could be seen. Therefore eliminating tweets that include keywords from the undesirable category is likely to eliminate some tweets relevant for emergency services. For example, "Winds strongly rushing, trees falling, roofs flying, power outing, and heavily raining here in Ormoc, Leyte. God protect us all! #YolandaPH" is a tweet relevant for emergency services and if undesirable keywords were used to eliminate this based on the word "God", it would have eliminated an otherwise disaster relevant tweet. Therefore it can be suggested that although not relevant keywords can assist in identifying irrelevant tweets, they should not be used on their own.

Overall, the findings from keyword distribution in Yolanda dataset is opposite of the findings from #qldfloods dataset. In #qldfloods it was identified that desirable keywords may not be a strong indicator of a disaster relevant tweet but the existence of undesirable keywords can be used to differentiate whether a tweet is relevant or irrelevant for emergency services. Findings from keywords distribution in the Yolanda dataset suggest that desirable keywords are likely to be an indicator of relevance and undesirable keywords are likely to be present in all categories. This difference confirms the issue of word sense disambiguation and it can be argued that keywords alone would be insufficient to determine if a tweet is relevant for emergency services.

5.4.4 Summary of findings

After applying the same set of automated tools on the Yolanda dataset it can be seen that it is difficult to use a single feature set to identify if a tweet is relevant for emergency services. Although each feature could identify some tweets that are relevant for emergency services, none of the features were self sufficient.

Images were found to be a very useful tool to separate disaster relevant tweets from irrelevant ones. Specific location names are also important as they can successfully identify tweets that are relevant for emergency services. In terms of keywords, filtering with irrelevant keywords provide better results than filtering based on relevant keywords as keywords relevant for emergency services also appear frequently in non relevant tweets.

5.5 Summary of Findings from Automated Analysis

The objective of this chapter was to use a set of tools to automatically identify four key features (image, location, desirable and undesirable keywords) that can suggest if a tweet is relevant for emergency services after a natural disaster. The aim of this tool set was not to completely filter out the tweets but to reduce the number of tweets to small enough number for emergency services to manually look over. These tools were tested on two datasets, #qldfloods and Yolanda and this section summarises the findings from these datasets based on each of the four features.

Image Based on the findings from both the datasets, if the tweet had an image that is shared either from a leading third party image sharing website or embedded from twitter itself, there was a high chance that the tweet was relevant for emergency services. However having an image does not necessarily guarantee that the tweet is relevant for emergency services. It is only useful to suggest that it is potentially relevant. Even after finding that a tweet has an image, other features needs to be looked for to determine if the tweet is relevant for emergency services or not.

Specific locations Specific locations were seen to be a better marker than image and retweet. However, similar to other markers of relevance, it is not usable as a single tool. Although the Stanford Named Entity Recogniser was often successful in identifying various named entities, it still needs to be filtered for country specific location names. If all location results are taken into consideration without filtering country level names, it is likely to increase false positives rather than finding relevant tweets.

Keywords relevant for emergency services Any keyword that is potentially relevant for emergency services was present in both relevant and not relevant categories in both datasets. Therefore using disaster relevant keywords as a filtering feature is likely to include tweets irrelevant for emergency services. Although keywords still remain a potentially relevant feature for emergency services to identify disaster related tweets, based on the findings from both the datasets a list of keywords relevant for emergency services were not proved to be useful.

Irrelevant keywords for emergency services A list of irrelevant keywords for emergency services on the other hand was proved to be very useful in filtering irrelevant tweets from both the datasets. However if this is the only filtering tool used it is likely to eliminate some tweets that are relevant for emergency services.

It is important to note that none of these should be misunderstood as a single filtering tool. They can be used as part of multi factor coding tool that can categorise incoming tweets in categories that emergency services deem relevant or irrelevant. Based on the findings from this phase it can be suggested that a combination of all the four features can potentially identify which group an incoming tweet may go to. Therefore in next chapter this multi-factor combined tool set is discussed.

Chapter 6: Discussion

The dissertation so far has explored if it is possible to identify whether a given tweet is relevant for emergency services after a natural disaster. This is because the main goal of the study is to **help emergency services to identify disaster relevant tweets in real time**. The objective is, instead of evaluating thousands of tweets after a natural disaster and getting overwhelmed, emergency services need to evaluate only a handful of tweets that are likely to be relevant for them.

Before continuing a description of a generic disaster management control room would be useful to situate this study. Generally a disaster control room will have a number of screens monitoring various channels related to the event. Some of these might be data from sensors, some could be reports from other agencies such as weather departments, and some channels could be media reporting on the disaster. A recent addition in these monitoring tools is social media monitoring, which is being used to gather intelligence (such as reports of damage), as well as to find out who may need help, or the reaction from the community. All of these channels are used at the same time to assist emergency services to make decisions that can save peoples lives.

This dissertation is situated in the social media monitoring segment of emergency services control room that is described above. The problem with using social media to gather intelligence or find who needs help is that the amount of tweets that get generated after a natural disaster is far too many for emergency services to evaluate. In addition, these tweets appear at an extreme pace. Therefore, this dissertation looked at how the number of tweets can be reduced to a manageable size so that emergency services can look at them.

In order to do so, Chapter Two evaluated literature to find out what type of information emergency services consider as relevant after a natural disaster and found three categories (Report, Request and Reaction). Chapter Three discussed the methods of gathering and analysing Twitter datasets. Chapter Four used qualitative methods to manually identify how often relevant tweets appear and what features are likely to be able to identify if a tweet belongs to these three categories. Chapter Five took these features and applied them to a larger dataset using automated tools. In the Chapter Four analysis of the dataset it was found that Report of Damage was the most prominent category among the categories that was relevant for emergency services. For this reason during the automated analysis in Chapter Five, the input data was focused on the Report of Damage category.

Based on the findings it can be seen that relevant tweets are likely to contain mention of specific locations, links, or embedded images. They also contain desirable keywords, although these keywords are also present in the irrelevant categories such as spam or personal narrative. The findings also indicate that the existence of undesirable keywords can be a good indicator of tweets being irrelevant. In addition, other features such as parts of speech are not good indicator to identify if a tweet is likely to be relevant for emergency services.

However, based on the findings, it can also be seen that a single feature is insufficient to automatically identify if a tweet is disaster relevant. Therefore this chapter combines the features discussed above and tests several combinations to present a number of subsets of tweets that emergency services can choose from. Instead of looking only for image, or only for location or keywords, this chapter combines all four features by assigning a score to each of the features to create a relevance score for each tweet using multiple linear regression, as described in Chapter Three. Using this relevance score emergency services can then operationalise this framework in order to narrow down the number of tweets they receive. Using this scoring system, each incoming tweets gets a score based on the formula and emergency services can choose to sort and look at the top 100 tweets or choose to look at a subset of tweets that reaches a certain relevance score. By doing this, emergency services can reduce the number of tweets to a manageable quantity in order to gather intelligence about the status of the disaster or assist people in need. The following section revisits the sub research questions to explain the findings and why the features are combined.

6.1 Sub RQ1: Identifying Relevant tweet for emergency services

The primary question for this research is **what type of tweet is considered relevant by emergency services after a natural disaster**. Since relevance is a subjective term it is a problematic topic to address. Therefore to explore this, literature related to emergency services were consulted to identify what is considered relevant information by emergency services after a natural disaster. Based on the literature, it can be suggested that there various types of information emergency services look for after a natural disaster. They include which areas are affected, how much help is needed, what type of help is needed and is it possible to reach that place with usual transportation methods. Identifying priority areas are important to ensure help is reaching in the right areas. It is also a priority for emergency services to be aware of the early volunteers in order to integrate them into the relief and rescue operation. . Thus, these are the information that is considered relevant for emergency services after a natural disaster.

Therefore, obtaining information from social media to assist with such assessments would be useful. However gathering actionable information is a challenging task. That is why in recent years emergency services have been looking at social media to find this information. Unfortunately this is such a new area for emergency services that present social media guidelines by emergency services only focus on information dissemination rather than information gathering.

Numerous academic studies however have attempted to address the lack of guidelines with regards to information gathering from social media (Bruns, Burgess, Crawford, & Shaw, 2012; Imran, Elbassuoni, Castillo, Diaz, & Meier, 2013; Lau, Tao, Tjondronegoro, & Li, 2012; Murthy & Longwell, 2013; Panem, Gupta, & Varma, 2014; Starbird, Palen, Hughes, & Vieweg, 2010; Vieweg, 2012). This has resulted in creating various types of information categories and coding categories. Among them some of the most relevant ones for this research are created by Vieweg (2012) and Bruns et al. (2012) which were described in Chapter Two. However these coding categories usually identify what is in the tweet rather than what information emergency services look for from the tweets. Therefore, during the course of this research the categories from Bruns et al. (2012) and Vieweg (2012), as well as the needs from disaster management literature, were combined to create the coding category, 3R - **Request, Report, Reaction,** to assist to find tweets that are relevant for emergency services.

Request deals with information that is related to help seeking behaviour. It can be seeking basic amenities such as food and water, medical assistance, seeking shelter or seeking information such as on amissing person. As long as the user is seeking something, it is grouped under Request.

Report on the other hand is the information provided by people with regards to the damage caused by the disaster. It can be a report about their personal property, public property, or environmental destruction.

Reaction is mostly about community self reporting in response to the situation. This can be of two types; one is about reactions regarding the efforts of emergency services and the other is about the volunteers who are often the first responders after a natural disaster. As it is identified by the literature as something emergency services look for, identifying such reactions is also included as relevant for emergency services.

However, existence of a Request, Report, or Reaction may not always be relevant if they do not contain priority or specific information. For example someone reporting about slight change of the floodwater has less priority then someone reporting about a building collapsing in the water next to a particular street. Therefore in order to identify which information is more relevant for emergency services, **Specificity** and **Urgency** were introduced.

A strong relationship between existence of **four features** and the tweet being relevant for emergency services was found after analysing the tweets from the #qldfloods and Yolanda datasets. Based on the manual analysis using the coding categories as well as specificity and urgency, **including images, locations and desirable keywords and not having undesirable keywords** were identified as markers that can determine if a tweet is relevant for emergency services.

In addition it was also found that among the three categories, the Report category, and especially Report of Damage, had the highest percentage of high ranked tweets. Therefore in the automated section the focus was to find these features automatically in order to determine if the tweet was likely to fall into the Report of Damage category.

6.2 Sub RQ 2: Identifying relevant tweets automatically

The second component of the central research question of this dissertation is to **automatically identify if a tweet is likely to be disaster relevant**. In Chapter Four it was found that identifying existence or non existence of four features indicate disaster relevance of a given tweet. In order to automatically identify tweets that are relevant for emergency services, the automated analysis phase employed various tools to find these four features in the tweets. As mentioned in the previous section, as Report of Damage had the highest percentage of disaster relevant tweets among the Report, Request and Reaction categories, the focus was limited to findings tweets that fall in the Report of Damage category. However when the set of tools were run through both the #qldfloods and Yolanda datasets for each of the four features, it resulted in both positive and negative findings. These are discussed in more detail below.

6.2.1 Existence of image

The results of this study indicate that tweets in the Report of Damage category (damage of infrastructure, environment, public, private property) had a higher proportion of images compared to other categories. Even though having an image does not mean that the tweet is relevant for emergency services or belongs to Report of Damage category, it increases the chances significantly.

The proportion of images is dependent on the type of disaster, and other circumstantial factors (e.g., the time of day the disaster strikes). In addition, the presence of images may increase over time as more people have smartphones. However the findings suggest that the existence of an image is an important marker of relevance for disaster relevant tweets. In case of the misuse of a hashtag to post images that might be irrelevant, it should still be scored highly to increase the chance that it be evaluated by emergency services so that emergency services can discard those irrelevant tweets.

6.2.2 Specific location

In both datasets that were analysed, finding specific location information proved to be a good marker of relevance for emergency services. Eliminating generic names such as country, city or large suburbs improved the chance of finding specific locations.

However using string generic name filtering may not work in all disasters. In other disasters such as in a tornado, the locations might need to be filtered by suburbs. And in the case of floods, named entities may need to include the whole suburb. Therefore having a fixed formula that identifies or eliminates certain type of locations is likely to introduce errors into the results.

This can be addressed by introducing a set of rules that uses geographical information systems to look for locations based on the type of disaster in progress.

If the disaster in question covers large areas (such as a tsunami or earthquake), the system may eliminate country and state names but focus on cities. In the case of a smaller scale disaster, the system can focus on the suburbs and include cities in the list of names that is considered generic. Therefore by introducing a dynamic list, it can include and exclude location names in specific and generic categories.

6.2.3 Desirable keywords for emergency services

Although keywords are the components that puts the tweet into a context, as a word can have many different meaning, finding the right context based on the keyword alone is a complex challenge. This was seen from the findings of the desirable keywords. Keywords that were identified as desirable for emergency services through manual analysis were found to create mixed results in automated analysis. From the findings from the Yolanda dataset it was found that desirable keywords were present in higher percentages in categories that were relevant for emergency services. However, in the #qldfloods dataset desirable keywords were not present in high percentage in the relevant category.

However, as Yolanda had a larger number of tweets to evaluate and the existence of desirable keywords were more prominent in the Report of Damage (Infrastructure Damage) category, it is possible that existence of desirable keywords indeed be an important marker of relevance. In addition, the analysis only used a small set of keywords that were identified through manual analysis to be disaster relevant. Extending such keywords by introducing a public dictionary where researchers and emergency services can add relevant words may improve the results.

6.2.4 Undesirable keywords for emergency services

Similarly, undesirable keywords were found to be more suitable to identify irrelevant tweets in #qldfloods. However in the Yolanda dataset undesirable keywords were present in all categories in almost equal percentages. On the other hand, in #qldfloods they were present mostly in categories that had irrelevant tweets. Therefore similarly to desirable keywords, a public dictionary of undesirable keywords may enhance the results.

Overall as it can be seen from the findings from the automated analysis in Chapter Five, none of the features can identify disaster related tweets alone even though each feature carries certain characteristics that can help to identify if a tweet is relevant for emergency services. Therefore in the next section, an approach for combining these features to evaluate the likely relevance of each tweet to emergency services personnel is presented. By generating a relevance score for each tweet this approach can be used to select a subset of tweets for closer manual review.

6.3 Combining Features

In the methodology chapter it was mentioned that for combining multiple features, multiple linear regression (Culotta, 2010) is as it is used by other researchers to analyse posts in social networks and search engine queries to predict crisis related situations (Abel & Houben; Bodnar & Salathé, 2013).

Therefore this section uses the multiple linear regression formula to identify a total relevance score from each tweet. In order to do so, it multiplies each of the features with their respective coefficient and combines them to create a score.

$$y_i = \beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + \ldots + \beta_p X_{ip} + \varepsilon_i$$

From the discussions so far in this dissertation the features that can be used as X_{i1} To X_{ip} have already been identified. They are: **RT, image, location, desirable keywords and undesirable keywords**. However, the coefficients to use β_j (To β_p) with them is not determined yet. As discussed in the methodology chapter, a regression coefficient can be identified using the difference between the random chance of tweet being disaster relevant and the chance of tweet being disaster relevant when a specific feature is present.

In order to find the regression coefficients, firstly the random chance that a tweet is likely to be disaster relevant must be identified. This is followed by then finding the chance of a tweet being relevant if any of the specific features exist in the tweet. After that, their difference is calculated to identify the regression coefficient.

6.3.1 #qldfloods dataset

As mentioned earlier, the first step in identifying the regression coefficient is to identify the random chance that a tweet is relevant for emergency services and then how much improvement each of the features make. Therefore, this section identifies for the #qldfloods dataset the chances that a tweet is relevant and the increase or decrease in chances for each of the variables. For the purpose of coefficient identification the same sample from the automated analysis was used. As mentioned earlier, retweets were removed from this sample.

Identifying random chance in #qldfloods   The #qldfloods dataset that was analysed in Chapter Four and Five, was divided in four categories. Among them, three were relevant to emergency services and the rest were grouped under Others, which included spam, personal narrative or other tweets that were considered as irrelevant for emergency services. All tweets (without RT) from the #qldfloods sample could be separated into the following breakdown (Table 15).

Theme	Coding Categories	Tweet Count
Report	Report of damage	241
	Reporting community behaviour	89
Request	Request for information	19
	Request for material support	11
	Request for other types of help	5
Reaction	Reaction from community	145
Others	Other not relevant categories	810
Total		1320

Table 15: Tweet counts in their coding categories (#qldfloods)

In order to determine the chances a random tweet belongs to a certain category this data can be utilised to create a probabilistic estimation. Since the categories are not dependent on each other, this estimation utilises an independent probability formula. The probability that any tweet belongs to a certain category can be calculated by dividing tweets from that category by the total number of tweets in the dataset. For example, to find out the probability that a random Tweet is about report of damage it can be written this way:

$$\textbf{P (Report of Damage tweet) =} \frac{damageTweets}{totalTweets}$$

Here, the probability that a given tweet is a tweet about damage is calculated based on total count of tweets that has been identified as damage tweet divided by total tweets available. Using the formula, the P (damage tweets) = 18.25% which means, for the #qldfloods dataset, if a tweet is picked randomly, there is a 18.25% chance that this tweet is going to be a Report of Damage tweet.

The same calculation is extended to other categories and based on this calculation, Table 16 shows that, there is a high chance that any random tweet is likely to be a tweet from another group instead of from the Request for Material Support category. This is because there is less than 1% chance a tweet is a request for material support while in the irrelevant categories this has a 61.36% chance of occurring.

Theme	Coding Categories	Probability calculation	P (tweet in this coding category)
Report	Report of damage	241 /1320 =	18.25%
	Reporting community behaviour	89 /1320 =	6.74%
Request	Request for information	19 /1320 =	1.43 %
	Request for material support	11 /1320 =	0.83%
	Request for other types of help	5 /1320 =	0.37%
Reaction	Reaction from community	145 /1320 =	10.98%
Other	Other not relevant categories	810 /1320 =	61.36%

Table 16: Independent probability of a tweet belonging to a certain coding category (#qldfloods).

As mentioned earlier and can be seen from the table above, Report of Damage is the largest category among all those that are relevant for emergency services. Therefore the rest of the chapter uses the Report of Damage category as the benchmark to find if having a specific feature increases the chance of being relevant to emergency services compared to random chance.

Increasing the chance of being in the Report of Damage category with specific features Four features have been discussed in detail in this dissertation as markers that can identify if a tweet is likely to be relevant for emergency services. The next step is to find out if having these specific features increases the probability that the tweet is likely to fall in the Report of Damage category. As mentioned in the methodology chapter, this can be calculated using **conditional probability with dependent** events using following formula.

$$\mathbf{P\ (E2\ |\ E1) =} \frac{P(E2\ and\ \ E1)}{P(E1)}$$

Probability increment with the image feature To find the conditional probability, first it is necessary to understand what is being looked for. In the automated analysis chapter it is already found that it is possible to identify if a tweet has an image. Therefore the question is, if it is found that the incoming tweet has image, what are the chances that it will fall in the Report of Damage category?

By putting this information in the formula, it can be seen that E1 is the image and E2 are the tweets that belong to the Report of Damage category. Therefore the formula can be re written in this way:

Probability of a tweet being in the Report of Damage category because it has image = Probability of a tweet that both has an image and is in the Report of Damage category divided by the probability of a tweet having an image.

Based on the counts in Table 17 it can be seen that the probability of image p(E1) is 153/1320, and P(E2) probability of a tweet that has both image and falls in the Report of Damage category is 83/1320. Therefore, the probability can be written as:

$$\textbf{P (Report of Damage | Image)} = \frac{\frac{83}{1320}}{\frac{153}{1320}} = \frac{83}{153} = \textbf{54.25\%}$$

Type of URL	Report of damage	All other groups	Total
Image	83	70	153
Other URL or No URL	158	1009	1167
Total	241	1079	1320

Table 17: Tweet counts based on Report of Damage and images

This means that for a random tweet that is picked from the group of tweets that has an image in them, there is a 54.25% chance that the tweet is a damage report. This is better than 18.25%, the random chance that a tweet belongs to the Report of Damage category and confirms that for the #qldfloods dataset, tweets that have an image are more likely to be disaster relevant. Similarly, when **P (Report of Damage | Not Image)** was calculated, it was found to be 13.25%. The same formula is now applied to the other categories. However for brevity, the entire explanations are not repeated for each of the features.

Probability increment with Specific Location Similar to image, count of tweets that have a location is detailed in Table 18. Using the above formula, it can be calculated that, **P (damage tweets | specific location) = 59/132 = 44.06%.** And, **P (damage tweets | Generic or no location) = 182/1188 = 15.32%.** This confirms that if the tweet contains mention of a location the probability of that tweet being in Report of Damage category is higher than random chance of it being in that category. And if it does not have a mention of a specific location, the probability is lower than the random chance.

Type of location	Report of damage	All other groups	Total
Generic location or no location	182	1006	1188
Specific location	59	73	132
Total	241	1079	1320

Table 18: Tweet counts based on their location

Probability reduction with keywords from the undesirable keyword list Table 19 lists the count of tweets that had any word from the undesirable list of keywords. Based on the calculation **P (damage tweets | undesirable keyword) = 9.26%** and **P (damage tweets | not undesirable keywords) = 19.06%** it can be seen that if a tweet has undesirable keywords, it reduces the probability of it being a tweet about damage by half.

Type of Keywords	Report of damage	All other groups	Total
No undesirable keywords	231	981	1212
Undesirable keywords	10	98	108
Total	241	1079	1320

Table 19: Tweet counts based on undesirable keywords list

Probability increment with a keyword from the desirable keyword list Using the same formula to only keywords that belong to the Report of Damage category (Table 20), it can be seen that **P (damage tweets | damage words) = 21.06%** and **P (damage tweets | other words) = 16.44%.** This suggests that for the #qldfloods dataset having desirable keywords did not increase the chance that a tweet is likely to be a Report of Damage significantly.

Type of Keywords	Report of Damage	All other groups	Total
Words from Report of Damage category (desirable keywords)	109	408	517
Other words	132	671	803
Total	241	1079	1320

Table 20: Tweet counts based on desirable keywords list

Comparing probability with random chance When all the probabilities are combined (Figure 49) it can clearly be seen that the image and specific location features significantly increase the probability of a tweet being in the Report of Damage category and therefore of being relevant for emergency services. Desirable keywords do not increase the chance that a tweet is likely to be relevant for emergency services, but undesirable keywords reduce the probability by almost half.

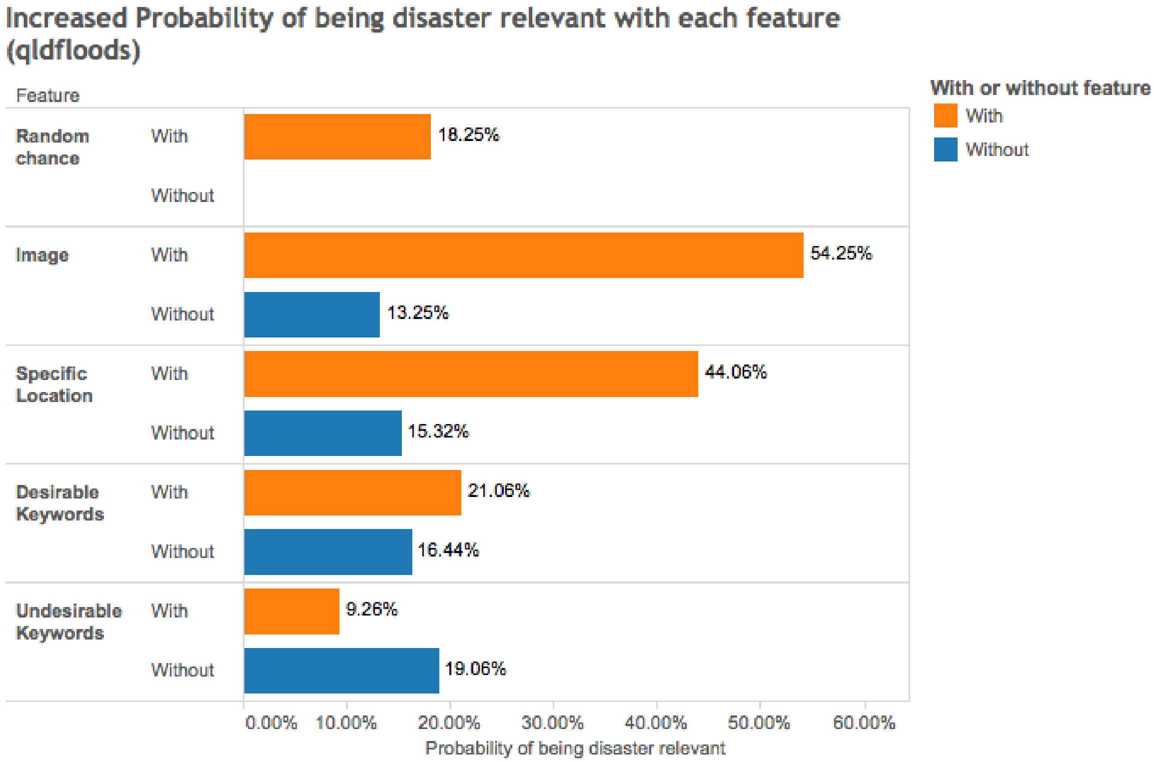


Figure 49: Comparing probability of tweets with and without features with random chance (#qldfloods)

Calculating regression coefficient Previously in Chapter Three it was mentioned that one of the way to identify regression coefficients is to find the division between random chance and conditional probability of each of the features. Table 21 lists all the conditional probability outcomes that have been discussed in this section. To evaluate the difference from random chance, each conditional probability was divided by the random chance to find their difference.

As it can be seen from Table 21, by including an image the probability of a tweet increases significantly and by not having image, it reduces the probability. The difference between the probability score with image is 2.97 times more than random chance and 0.72 less than random chance for without an image. Both of these values can be used as a regression coefficient.

	Probability a tweet is related to damage	**Difference from random chance**
Random chance to be tweet about damage	18.25%	N/A
With image	54.25%	2.97 ▲
Without image	13.25%	0.72 ▼
With specific location	44.06%	2.41 ▲
Without specific location	15.32%	0.83 ▼
With desirable keywords	21.06%	1.15 ▲
Without desirable keywords	16.44%	0.9 ▼
With undesirable keywords	9.26%	0.5 ▼
Without undesirable keywords	19.06%	1.04 ▲

Table 21: Random probability and difference with random chance in #qldfloods dataset Similarly to the image feature, for a random tweet that is picked from the group of tweets that has a specific location in them, there is a 44.06% chance that the tweet is a damage report. This is 2.41 times more than the random chance identified in Table 21. For tweets that do not have a specific location, the chance that it belongs to the Report of Damage category is lower than the random chance. By calculating the values, it can be seen that it is 0.83 times less, which means the chance is further even reduced. Similarly to the image coefficient, this difference is used as the regression coefficient in the combined features.

However, having desirable keywords related to damage only increases the probability by 1.15 times. In comparison, not having desirable keywords from the damage list reduces the chance very slightly (0.9 times). Based on the calculation it can be suggested that words from the desirable keywords list introduces a small positive correction, but does not improve the chance dramatically.

Conversely, having word from the undesirable keyword list reduces the probability that the tweet is relevant to emergency services. If there is an undesirable keyword in the tweet, it reduces the chance that the tweet may belong to the Report of Damage category by 0.5 times. However, if there are no undesirable words it does not increase the probability significantly – the chance increases from 1 to 1.04 times. In order to create a regression coefficient that is not only limited to the #qldfloods dataset, the same steps were applied to the Yolanda dataset as well.

6.3.2 Yolanda dataset

To identify random chances and regression coefficients from the Yolanda dataset, the same **22,084 tweets** that were used in Chapter Five were used in this section. The initial 230,000 tweets were reduced to this number based on the agreement percentage, retweet removal and time of capture as is explained in Chapter Four and Five. Similar to the #qldfloods dataset, the process was to identify the random chance, followed by finding conditional probability of each of the features against a category that matches the coding category of Report of Damage in the Yolanda dataset, Infrastructure damage.

Identifying random chance in Yolanda Similar to #qldfloods, the first step was to find out the random chances for a tweet in Yolanda tweets. Using the **P (Tweet in coding category) =** $\frac{tweetsWithFeature}{totalTweets}$ the probability of a given tweet to be in that category can be seen from Table 22.

Once the random chance has been identified, the next step is to find the probability with or without the identified features. In order to keep it consistent with the #qldfloods analysis as well as to compare, the coding category used from Yolanda dataset was Infrastructure Damage, which is also about reports of damage. In the remainder of this section the conditional probability of a tweet being in the Infrastructure Damage category is calculated for each the features.

Theme	Coding Categories	Tweets in the category	Probability calculation	P (tweet in this coding

				category)
Relevant	Infrastructure damage	295	295 / 22,084 =	1.33%
	Request for help	420	420 / 22,084 =	1.9 %
	Population displacement	67	67 / 22,084 =	0.3 %
Irrelevant	Not English	2,303	2,303 / 22,084 =	10.43 %
	Relevant but other	1,477	1,477 / 22,084 =	6.68 %
	Not relevant / Skip / RT	17,522	17,522 / 22,084 =	79.34%
Total		22,084		

Table 22: Independent probability of a tweet belonging to a certain coding category in Yolanda tweets

Once the random chance has been identified, the next step is to find the probability with or without the identified features. In order to keep it consistent with the #qldfloods analysis as well as to compare, the coding category used from Yolanda dataset was Infrastructure Damage, which is also about reports of damage. In the remainder of this section the conditional probability of a tweet being in the Infrastructure Damage category is calculated for each the features.

Probability increment with image feature The same formula that is used in qldfloods dataset is used with images in Yolanda to identify **P (infrastructure damage tweets | image)**. Using the values listed in Table 23 it can be seen that **P (infrastructure damage tweets | image) = 3.33%** and **P (damage tweets | not image or other URL) = 1.2%**

Type of URL	Infrastructure damage	All other groups	Total
Image	36	1,043	1,079
Other URL or No URL	259	20,746	21,005
Total	295	21,789	22,084

Table 23: Tweet counts based on Infrastructure Damage and image

Probability increment with Specific Location Using the same formula, it can be seen from Table 24 that, **P (infrastructure damage tweets | specific location) = 4.11%** and, **P (infrastructure damage tweets | Generic or no location) = 0.89 %.**

Type of location	Infrastructure damage	All other groups	Total
Specific location	123	2,804	2,927
Generic location	172	18,985	19,157
Total	295	21,789	22,084

Table 24: Tweet counts based on Infrastructure Damage and location

Probability reduction with undesirable keywords Using the same formula to not relevant keywords, it can be seen (Table 25) that **P (infrastructure damage tweets | undesirable word) = 0.76%** and **P (infrastructure damage tweets | other words) = 1.42% .**

Type of Keywords	Infrastructure damage	All other groups	Total
Undesirable keywords	24	3,103	3,127
No undesirable keywords	271	18,686	18,957
Total	295	21,789	22,084

Table 25: Tweet counts based on Infrastructure Damage and undesirable keywords

Probability increment with desirable keywords Applying the same formula to only desirable keywords, it can be seen (Table 26) that **P (infrastructure damage tweets | desirable keywords) = 6.4%** and **P (infrastructure damage tweets | other words) = 0.55%**

Type of keywords	Infrastructure damage	All other groups	Total
Desirable keywords	189	2,938	3,127
No desirable keywords	106	18,851	18,957
Total	295	21,789	22,084

Table 26: Tweet counts based on Infrastructure Damage and desirable keywords

Comparing probability with random chance Similar to #qldfloods, when the probabilities are compared it can clearly be seen that the image and specific location features significantly increase the probability of a tweet being about infrastructure damage. Although desirable keywords in the #qldfloods dataset did not result in significant increases in the chance of a tweet being about Report of Damage, in the Yolanda dataset, it can be seen that tweets that had desirable keywords are more likely to be disaster relevant. Undesirable keywords on the other hand were not as good of an indicator as in #qldfloods to identify irrelevant tweets.

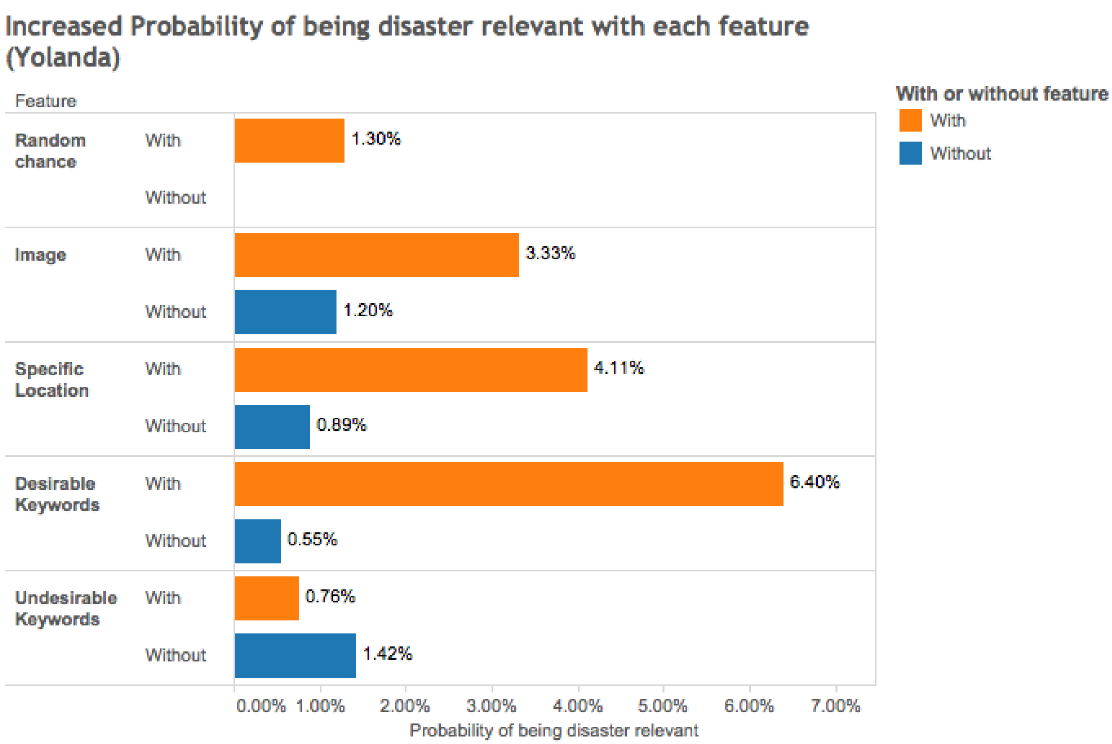


Figure 50: Comparing probability of tweets with and without features with random chance (Yolanda)

Calculating regression coefficient Similar to #qldfloods, the coefficient is calculated by dividing the conditional probability score of each feature by random chance. While a random tweet has a 1.3% chance of being in the Infrastructure Damage category, with images, the chance increases by 2.56 times, while not having an image reduces the chance by 0.9 times. Both of these values are used as coefficients.

	Probability of a tweet to be about infrastructure damage	Regression coefficient
Random chance to be tweet about infrastructure damage	1.3%	N/A
With image	3.33%	2.56 ▲
Without image	1.2%	0.92 ▼
With specific location	4.11%	3.16 ▲
Without specific location	0.89%	0.68 ▼
Desirable keywords	6.4%	4.92 ▲
Without desirable keywords	0.55%	0.42 ▼
Undesirable keywords	0.76%	0.58 ▼
Without undesirable keywords	1.42%	1.09 ▲

Table 27: Random probability and regression coefficients of Yolanda dataset

As it can be seen in the Table 27, using specific location improves the probability by 3.16 times. On the other hand, having a generic or no location reduces the probability by 0.68 times. Although the reduction is close to #qldfloods dataset (0.8 times), the probability of finding an infrastructure damage tweet given it has a specific location is higher (2.41 times in #qldfloods dataset). This suggests that such multiplier values need to be adjusted depending on the dataset. Therefore an average of these scores is used in the final coefficient, which is described in the next section.

Undesirable keywords however only reduced the chance that the tweet is about infrastructure damage by 0.58 times. This is different than #qldfloods where the presence of an undesirable keyword was seen to be a better identifier of irrelevant tweets as it reduced the probability by 50%. Similar to the #qldfloods dataset, in Yolanda dataset not having an undesirable keyword in the tweet makes the probability that a given tweet is about infrastructure damage 1.42%, which is only

1.09 times more than the 1.3% random chance. One key point to note is, for the Yolanda dataset, a lot of the words that are not relevant for emergency services such as prayer or God were included as a part of the hashtag (e.g., #prayForPhilippines). Such words were not counted as they were part of a multi-word combination. It is possible that including them will further increase the quality of the algorithm.

The biggest difference with the #qldfloods dataset is in the category of desirable keywords. As it can be seen from Table 27 and Figure 50, if there is a desirable keyword in the tweet, it is 4.92 times more likely to be an infrastructure damage tweets than by random chance. At the same time, if it does not have desirable keyword it reduces the chance by 0.42 times. Both of these values are higher than the #qldfloods dataset as the existence of desirable keywords in that dataset increased the probability that the tweet is a report of damage by only 1.17 times more than random chance. The issue with this finding is that word sense disambiguation is a known and well established problem and relying on keywords is likely to deliver error prone results. Therefore, using this as a part of the multi factor combination is likely to result in a more reliable output rather than relying on the single feature alone.

6.3.3 Combined regression coefficient

A combination of the random probability and regression coefficients is outlined in Table 28. A few observations can be made from this table. In #qldfloods the random chance that a tweet is likely to be in the Report of Damage category is much higher than Yolanda – 18.25% chance in #qldfloods compared to 1.3% chance in Yolanda. However, when the regression coefficients were calculated it was found that there is not a significant difference between the coefficients of both datasets. For example, with image as a feature, there is 2.97 times increase in probability in #qldfloods and 2.56 time increase in probability in Yolanda that the tweet is likely to be in the Report of Damage category.

The only notable exception was the coefficient for desirable keywords. In the #qldfloods dataset having desirable keywords only increased the chance by 1.15 times. However in Yolanda it increased the chance by 4.92 times. However, as discussed earlier, word sense disambiguation is a known problem and using average of 3.035 as coefficient is likely to introduce error in the result. Therefore the coefficient for desirable keywords were marked to 2.5. In addition, as the existence of location was found to be an important marker of relevance for emergency services, the average is increased to 3 even though the average of coefficient from Yolanda and #qldfloods is 2.75.

Dataset	**#qldfloods Regression coefficient**	**Yolanda Regression coefficient**	**Regression coefficient for testing**
With image	2.97 ▲	2.56 ▲	2.75
Without image	0.74 ▼	0.92 ▼	0.8
With specific location	2.41 ▲	3.16 ▲	3
Without specific location	0.83 ▼	0.68 ▼	0.75
Desirable Keywords	1.15 ▲	4.92 ▲	2.5
Without desirable Keywords	0.9 ▼	0.42 ▼	0.75
Undesirable keywords	0.5 ▼	0.58 ▼	0.55
Without undesirable keywords	1.04 ▲	1.09 ▲	1.06

Table 28: Calculating Regression coefficients for final experiment

However, it is important to note that for each event the coefficient is likely to be different. Given the objective of this research is not to find a specific regression coefficient that works in all situations but to test the viability of scoring method, the focus is how well the framework performs.

6.4 Result and Evaluation of Combined Features

This section presents the results of the combination of features. It evaluates if the total relevance score calculated by using the factors established in the previous section as coefficients in the regression calculation identifies tweets that are likely to be disaster relevant. In order to do so, this section first demonstrates how relevant scores are calculated for a given tweet. After that it explores the use of various cutoff scores to show how the number of tweets presented to emergency services can be affected by changing settings. This is then followed by an evaluation of the results based on the crowd coded tweets.

6.4.1 Scoring each tweet

In the earlier section several features were identified. In this section all the regression coefficients are developed. By applying both the variables and the regression coefficients, each tweet can now receive a score by using a multiple regression formula. For example, by using the formula scores of these two tweets are calculated in Table 29.

$$y_i = \beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + \ldots + \beta_p X_{ip} + \varepsilon_i$$

Tweet	Cnr Coro Drv and Hale St. Go-Between bridge on ramp #aquapocolypse #qldfloods http://twitpic.com/3p9jmq
Score	= 1 (specific location) * 3 + 1 (image) * 2.75 + 1 (no desirable keyword) * 0.75 + 1 (no undesirable keyword) * 1.06= 7.56
Tweet	Please keep my family friends + everyone in QLD Australia in your prayers. #QLDfloods
Score	= 1 (generic location) * 0.75 + 1 (no image) * 0.8 + 1 (desirable keyword) * 2.5 + 1 (undesirable keyword) * 0.55 = 4.6

Table 29: Calculating relevance score of sample tweets

As it can be seen from these two tweets, a tweet that is likely to be relevant for emergency services receives a higher score compared to a tweet that is likely to be irrelevant for emergency services. In the first place, this allows incoming tweets to be ranked according to their likely relevance. For example, tweets with a higher relevance score could be displayed more prominently to an emergency services staff member monitoring the full feed of tweets than tweets with a lower score.

Additionally, tweets with a lower relevance score could be excluded from the feed altogether, enabling the staff member to focus on the most relevant tweets only. Therefore by creating a cut off score it is potentially possible to reduce the amount of irrelevant tweets and only present a subset of relevant tweets to emergency services so that they can manually evaluate and decide which of them are relevant for them. The following part of this section discusses the effect of the cut off score.

6.4.2 Cut off score

To demonstrate how cut off score may help to reduce the number of tweets to a manageable amount for emergency services, the scoring is applied on the same 22,084 tweets from Yolanda dataset. As it can be seen in Figure 51, increasing the cut off score reduces the number of tweets that are considered relevant for emergency services. Based on the figure, in the first case where the cut off score was 3.0, the script considered 77% tweet as relevant for emergency services. When it was increased to 4.0, that number was reduced to 45% of the tweet count. By increasing the cut off even more, it reduced the tweet count even more and when the score was above 5.0, less than 3% of the tweets were above the cut off score. And of course, even within this reduced dataset tweets could be further ranked by their individual relevance score.

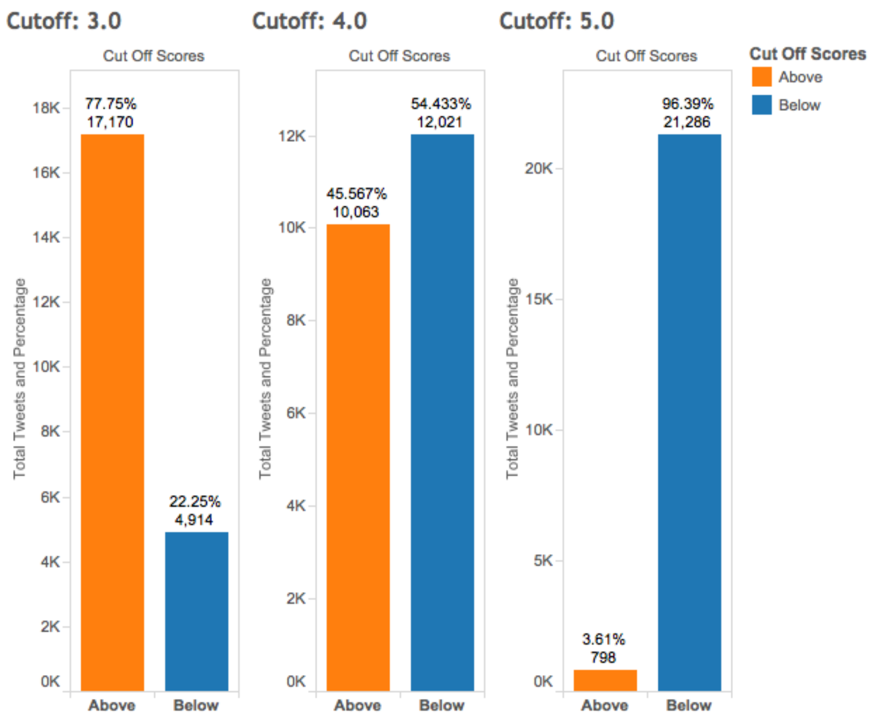


Figure 51: Change in count and percentage of tweets from Yolanda dataset based on change of cut-off score

The way this can help emergency services is that after a disaster when a large volume of tweets appear, emergency services can use a higher cut of score to limit the number of tweets they evaluate. If they have enough manpower or time, they can reduce the score so that they can receive larger subset of tweets, which may contain irrelevant tweets as well. And if they have even more manpower to read the tweets, they can reduce the cut off score to an even lower number to see even more tweet.

Another way emergency services can use this score is by sorting the tweets based on their scores. Even if they do not use a cut off score, they can identify the high scoring tweets to evaluate. In addition, these two approaches could also be combined.

6.4.3 Evaluating output of the system using MicroMapper coding

The question remains, are the subset of tweets that were above the cutoff score actually relevant? Since these 22,084 tweets from Yolanda were already categorised by MicroMappers, overlaying them on top of the output generated by the system can show if the algorithm has successfully identified relevant tweets. For the purpose of this illustration, cut off scores of 4.5 to 4.8 and 5.0 were used. Once the score is applied, only tweets that were above the score cut off were presented here.

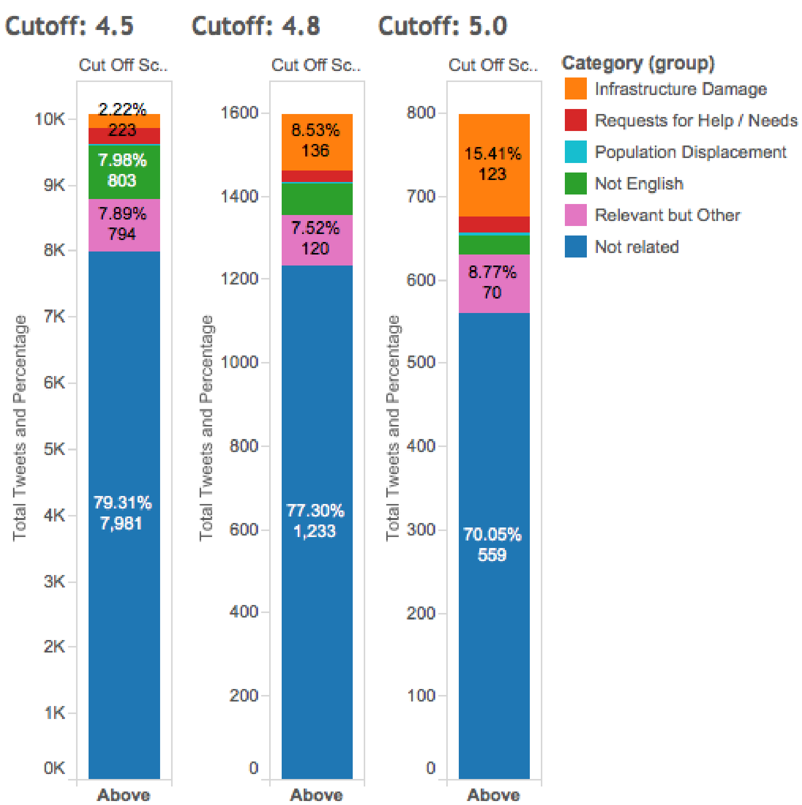


Figure 52: Change in percentage and count of tweets in above cut off score in their category

Based on Figure 52 it can be seen that when the cut off score was low, a lot of tweets that were identified as not relevant by MicroMappers were also included in the subset of tweets that require attention from emergency services. The higher the score, the lesser counts of not relevant tweets appear. For example, by increasing the cut off scores from 4.0 to 4.8, not relevant tweets were reduced from 7981 tweets to 1233 tweets.

At the same time, the proportion of tweets from potentially disaster relevant categories within the remaining dataset increases significantly with higher cut off scores. This demonstrates that the relevance scores developed in this thesis enable a targeted selection of potentially relevant tweets from the overall dataset.

It is also important to note that, when the cut off scores are increased tweets that are relevant, such as those in the infrastructure damage category, were also reduced. Therefore, the decision of which cut off score to use should be left to emergency services who can increase the score or decrease it based on the sample of tweets they would receive. If they see that by increasing the cut off score they are not receiving many relevant tweets, they can decrease the cut off score. Although this means increasing the number of tweets they need to look at, they ensure they do not miss tweets that are likely to be relevant.

At this point it needs to be restated that the objective of this research is not to find the perfect score. The objective is to provide an operationalisable framework for emergency services so that, as the experts in the field, they can decide for themselves what works best for them. If the agency only has a handful of people, they should increase the cut off score to receive only a small number of tweets but if they have a large team working with them, or are not pressed for time, they can reduce it to accept potentially irrelevant tweets as well.

6.5 Limitations

As it can be seen from the chart of cut off scores (Figure 52), the algorithm is not always accurate. Even though the cut off scores reduces irrelevant tweets, they still appeared in the subset of tweets that received enough scores to be above the threshold. This section below analyses the limitations and why it might have occurred.

6.5.1 Infrastructure damage

Some tweets that were classified as irelevant by the scoring method but were classified under the Infrastructure damage category by MicroMappers and vice versa. This section discusses some of the cases where such mismatch has occured.

Breaking news were included as infrastructure damage Tweets such as "#BreakingNews #YolandaPH Brownouts in Tacloban City confirmed by @cebutechblogger Bert Padilla. Read more updates at:http://_" is problematic because it was talking about breaking news. As the evaluators were people from all aspects of life, it is possible that they feel that breaking news about damage should be included as infrastructure damage. As it had both specific location name and keyword, it was identified as relevant as well even though breaking news is unlikely to be relevant for emergency services.

Location name in multi word hashtags was not picked up Another tweet that was considered as relevant for emergency services but was not picked up by the automatic scoring was "Typhoon-damaged Petron Gas Station. #RoxasCity #YolandaPH #HelpCapiz #RescuePH #Philippines http://t.co/yRJ4iB8uWT". There are two issues here, one is the image was not detected due to the deletion of the referred image and the second is the name of the cities were included in the multi word hashtag – Roxas City and Help Capiz. Although this issue can be addressed using other algorithm that separates multi words in their individual words, this went beyond the scope of this thesis and was not tested here.

Insufficient information was not picked up Another tweet that was identified as relevant was “Again no electricity. #YolandaPH”. This was marked as relevant for emergency services by many evaluators but was not picked up by the scoring system as it did not have sufficient information. Tweets such as these are a genuine issue as they do not contain enough information to be a source of information and increasing the weight of the words are likely to result in more false positives.

Overall, it can be seen that MicroMappers have occasionally marked irrelevant tweets as relevant. This can also be seen in the Request for Help category as well, which is described next.

6.5.2 Requests for help

Tweets that were classified as irrelevant by the scoring method but were classified under the Request for Help category had both genuine relevant tweets for emergency services as well as irrelevant tweets

Reaching prominent personnel In Phase One, reaching out to prominent persons was identified as a potential marker of relevance. However in Phase Two Part Two it was found that reaching out to prominent personnel may not necessarily result in tweets relevant for emergency services. This is potentially the reason why many evaluators have marked tweets such as “@SMARTCares please restore the services in Samar and Samar areas ASAP.#YolandaPH”, “@TheKhalilRamos #RescuePH #HelpTacloban help us po!” and “@TheKhalilRamos #RescuePH Ilo-Ilo needs help” as relevant for emergency services. These tweets were not identified as relevant based on their score but was identified as relevant for emergency services by the MicroMappers.

One adjustment that could be used is, if the tweet is trying to reach prominent user handles such as the Red Cross, it could be weighted higher. For example, “@philredcross Please help to find @ReneePatron, Sonny Patron and Remy Patron #tracingph #easternsamar #guiuan #YolandaPH” is relevant for emergency services and the reason it was not identified as relevant was because the scoring system only evaluated location names. If it were to calculate other named entities, it is likely to find this information as well.

This finding is similar to the finding of Part One of Phase Two, which finds that named entities may identify a place name such as building name as an organisation. Therefore as long as named entity identifies a word as place, organisation or a person it should be included as relevant for emergency services.

Uncertainty over inclusion Certain tweets did not have sufficient information or were vague in nature. For example, “Save the Filipino people's in Visayas #RescuePH” may appear relevant for emergency services by people but it is likely to be more of a personal narrative rather than a call for help. Similarly, a tweet which was classified as a request for help, “#Cebu volunteers needed in repacking relief goods. For those interested, call Ms. Evelyn Senajon at 254-7198 and 254-8397. #YolandaPH” is not really useful for emergency services because they are the one likely to be calling for help!

Overall, the approach of combining several features to produce a relevance score generates good results when evaluated against the work of the MicroMappers. Any discrepancies between the results produced by the algorithm and the MicroMappers’ evaluation are just as likely to be caused the MicroMappers as they are to be a sign of issues with the algorithm presented here. Further evaluation of this approach would therefore benefit from additional manual evaluation using a team of coders – but this is outside the scope of this thesis and therefore was not conducted.

6.5.3 Not relevant

There were interesting findings in the tweets that was marked as Not Relevant by people but received enough scores to be classified as relevant for emergency services by the scoring system. This section describes some of these tweets as well as identifies the false positives.

Criminal activity was grouped as not relevant In previous chapters reports of criminal activity was identified as relevant for emergency services. However there were several tweets about looting such as this tweet, “Heard about the massive looting in Gaisano Tacloban. So sad. #YolandaPH” that was identified as not relevant by MicroMappers. Since the initial guidelines (see Figure 17, pg. 106) did not ask people to look for such tweets, people might have included these as Not Related. However as it had enough variables in them, it received a relevance score to go beyond the cut off threshold.

Mentions of damage and information requests There were tweets that mentioned damage but that MicroMappers have identified as not relevant. For example, “my sister-in-law's house in brgy fabrica mobo masbate is ruined because of super typhoon yolanda. manay marites be strong & dont loose HOPE!” should have been included in the infrastructure damage category but was categorised under not relevant by MicroMappers.

Similarly, “#YolandaPH / #Haiyan: Power cuts here in our place, they closed the doors and I can hear crashing objects outside | @mikhaeladeleon in Leyte” also updates the current situation but was identified as not relevant by MicroMappers. However, as these tweets had a name of location, as well as words from relevant categories, they have received enough score to be counted as relevant for emergency services. Another tweet, “We desperately need updates from our families in Tacloban City. #YolandaPH #tacloban” was classified as not relevant by MicroMappers although it was clearly seeking for information, but the algorithm picked it up as potentially relevant for emergency services by assigning high score. This indicates that in such cases the automated relevance scoring algorithm may in fact be more accurate in detecting relevant tweets than the crowdsourced MicroMapping process.

Might be useful tweet One of the tweets, "here in Daet, Camarines Norte we are experiencing gusty winds and scattered rain showers #YolandaPH .prayers for those who will directly hit" was classified as relevant by the scoring system. The interesting part about this tweet is, although it is not relevant at the given moment, it might indicate a possible turn of the wind direction.

Based on the findings it can be seen that, in some instances the scoring system has outperformed the human evaluator in identifying tweets that should have been classified as relevant for emergency services.

6.6 Summary of Discussion

This discussion chapter started with addressing the research questions about finding what is relevant for emergency services and how these can be filtered automatically. Based on the findings of previous chapters some features were identified as markers of relevance for emergency services. This chapter combined them to create a framework that can filter out tweets that are relevant for emergency services from irrelevant ones.

By using multiple linear regression it included all the features that were previously identified to calculate total score of a tweet. After that, the result was compared with the crowd coded categories to find out how closely they resembled human coders. As it can be seen from the combination of features, the algorithm successfully generated a relevance score for each tweet in the dataset. This chapter has demonstrated that this score can then be used to rank tweets according to their relevance to emergency services, and to exclude tweets below a certain threshold score. Although it does not eliminate false positives and false negatives completely, it mimics the human evaluation closely. In addition, it was also found that in some instances human evaluators did not follow the instruction correctly as well, making a number of false positives and false negatives in the evaluation data itself.

Overall, findings from the combination of features suggest that it can be a useful tool for emergency services to monitor social media and use it to gather intelligence after a natural disaster. In the next and final chapter, the conclusions from these findings and potential for future research are discussed.

Chapter 7: Conclusion

This thesis set out to answer the research question: **How can information relevant to emergency services be identified from Twitter automatically during and following a natural disaster**. In order to do that, an automated method of evaluating whether an individual tweet may be relevant for emergency services following a natural disaster was developed and tested. The new algorithm resulted from iterative development and testing that assigns a relevance score to each tweet. This score was based on four extractable features from tweets that were identified as potential markers of relevance. Assignment of this relevance score enables emergency services to decrease the number of incoming tweets they need to review by using a cut off score to create subsets, or to sort them based on their score and review a certain top percentage of the tweets.

The algorithm was developed and tested using a series of applied research phases that ensure that the new procedure was developed systematically and iteratively. the key issues related to identifying information from social media were introduced in Chapter One. In Chapter Two, key literature was analysed to find out what is considered relevant by emergency services. Chapter Three discussed various existing methodological approaches and techniques used in identifying relevant information from large datasets with manual and automated analysis was selected to use in this research. The findings from manual analysis was presented in Chapter Four, through which a new set of coding categories (Request, Report, Reaction) and ranking (Urgency and Specificity) were proposed that can be used to group disaster relevant information. In addition to the new coding categories, four features were also identified that can be used to suggest to emergency services the potential relevance of an individual tweet. In Chapter Five, the process and results of an automated test of these four features (including the existence of images, specific location, desirable and undesirable keywords) using a larger dataset was presented in order to determine if these features could successfully identify disaster relevant tweets. Using the findings presented in Chapter Five, Chapter Six showed how all four features can be combined using a mathematical formula (multiple linear regression) to create the framework that can be used by emergency services to assign scores to each tweet. Using the scores, emergency services can then choose to evaluate a smaller subset of tweets that are likely to contain disaster relevant information, or sort incoming tweets based on their score to review top tweets.

In this final chapter, the project outcomes are summarised focusing on how these key findings contribute to knowledge, this is followed by a discussion of the limitations and potential directions for future research.

7.1 Implications and Contributions to Knowledge

In order to understand what makes a tweet relevant for emergency services after natural disaster, this research tapped into various disciplines ranging from crisis communication to computer science. Frameworks related to needs of emergency services helped to understand what is relevant for them; theories of media and communication helped to create coding categories that can be useful to look for that information through the lens of social media; and tools and frameworks from computer science helped to understand if this information can be identified automatically with minimal human intervention. The following subsections explain these contributions in further detail.

7.1.1 Crisis informatics

While reviewing disaster management literature, the need for actionable information has been mentioned repeatedly (Acar & Muraki, 2011; Bodenhamer, 2011). Suggestions to use social media during disasters to gain critical intelligence was also highlighted (Rothery, 2012). At the same time it was also mentioned that the task of finding actionable information from social media is extremely challenging (UNISDR, 2013). Coding categories by Vieweg (2012) and Bruns et al. (2012) offered ways to group such information based on where they occur (e.g., social environment, built environment) (Vieweg, 2012) or type of information (e.g. media sharing, personal narratives) (Bruns., et al., 2012).

By combining the information needs of emergency services and the coding categories, this research contributes to the current literature by proposing new coding categories that is not based on specific features or environment and therefore provide the flexibility of adopting future changes in features introduced by Twitter or norms adopted by Twitter users. The proposed coding categories suggest that information that is likely to be relevant for emergency services are either **Report**, which includes reports of damage, **Request**, which includes requests for help or basic amenities and **Reaction**, which includes community self reporting with regards to emergency services effort. These proposed categories extends current knowledge and understandings of what constitutes disaster relevance and hopefully can be used by crisis informatics researchers in the future.

7.1.2 Emergency services

The second contribution is the introduction of four key features and the process of combining these features that can be used by emergency services. The framework of combining features as well as the tool developed during this research can be applied by emergency services in their existing social media monitoring systems to gather important intelligence after a natural disaster.

These features were identified from manual analysis after the tweets were grouped using the coding categories and ranked based on **Urgency** and **Specificity**. Among these features, the existence of images and specific locations were found to be useful marker of relevance across both the datasets. The existence of desirable keywords were highly relevant in the Yolanda dataset but not so in the #qldfloods dataset. Similarly, the existence of undesirable keywords found irrelevant tweets in the #qldfloods dataset but was not effective for the Yolanda dataset.

However, the assignment of relevant score based on the combination of all the features using multiple linear regression was more effective in identifying disaster relevant tweets with high accuracy. In some cases it even outperformed crowd coded evaluation. The results of this study indicate that combining these features it is possible to automatically identify whether a tweet may be relevant for emergency services after a natural disaster. Using the output, emergency services can then choose to evaluate a subset of tweets to find disaster relevant ones. Depending on the human resources available, they can either lower the cut off score and evaluate a large number of tweets or increase the cut off score and only evaluate a small number of tweets. Overall, the algorithm and the framework of finding features and combining them can assist emergency services to use Twitter more effectively as a part of their social media monitoring system.

This novel finding contributes to the field of automatic identification of disaster relevant information from tweets. It extends existing methods of dictionary lookup, word sense disambiguation, part of speech tagging, counting frequency of unigram, and bigram (Valero, Gómez, & Pineda, 2009; Verma et al., 2011; Vieweg, Hughes, Starbird, & Palen, 2010; Vlachos, 2011) with the suggestion of focusing on image, mentions of specific location, and desirable and undesirable keywords. The combination procedure also proposes an alternative way of combining features than suggested by Gupta et al. (2012) or Huang et al. (2014).

7.1.3 Research process

Twitter research in general is increasingly becoming multidisciplinary, and the process used in this research can act as a guideline for future researchers who want to work in multidisciplinary Twitter research. The process of creating coding categories by manual evaluation and then applying the findings by developing an algorithm that performs better than random chance, can be adopted by other researchers working in the area of crisis communication, social media and large datasets.

Researchers can also utilise the method of using crowd coded evaluation to set benchmark and compare that with results from automated analysis in order to find out how well their system mimics human evaluation. As utilising crowdsourced data is gaining popularity (Liu, 2014; Rogstadius et al., 2013; Starbird, Muzny, & Palen, 2012), such a method can be useful approach for researchers.

7.2 Practical Uses

As an applied research project this research has a strong practical aspect. The final outcome of this research can be directly used by emergency services to integrate into their existing social media monitoring systems. In addition, machine learning systems that can analyse Twitter data can also use the features identified in this research to enhance their systems. The coding categories can also be used by emergency services to group incoming Twitter messages for further study and evaluation.

7.3 Limitations

The primary limitation of this research is that the method was evaluated on only two natural disaster events. Applying the method on other types of natural disasters such as an earthquake would have provided a more generalisable approach. Secondly, the manual analysis process was dependent on the researcher's coding decisions for one dataset and the crowd's decisions on another dataset; both of these can be improved. For example, although the crowd coding method is in itself innovative, there are no methods developed as yet for evaluating crowd coded data. Even though there is an increasing interest in the research community with regards to crowd coding, it is still in the early stages and requires more research. Thirdly, trend of using Twitter features to perform only specific task may change quickly. For example, with the increasing usage of the selfie in the social media, image might be replaced by some other feature that will indicate relevance. Fourthly, a system like this is always susceptible to trolls and mischief because it uses hashtags to gather data and hashtags are often trolled. If the trolls overtake the hashtag then the system is no longer useful, but it is common for users to create a new hashtag if the previous hashtag is not longer useful. Fifthly, the automated analysis of the datasets relied heavily on the researcher's programming ability and approaches and it is likely this automated phase of the process may be extended using alternative approaches developed by other programmers. In making this project open source, it is hoped that the findings of this research will be adopted by others interested in this area in order to extend and improve the outcomes. One example of such an improvement includes development of a more rigorous mathematical model that might reduce the false positives or false negatives that were seen in the findings from automated analysis phase. Lastly, as new users join Twitter, new features get introduced, spammers, scammers get smarter, trolling techniques improve; the current scoring system needs re-evaluation. Therefore for this system to be applicable in future, it needs to go through constant changes so that it is up to date and able to withstand the issues mentioned.

7.4 Future research

This section presents six potential directions for future research that could help progress the research on uses of social media and crisis informatics further.

7.4.1 Better quality location detection

Identifying specific location names were found to be one of the most important features to identify if a tweet is likely to be relevant for emergency services. However, even with the state of the art Stanford Named Entity tool, there were numerous errors.

One of the biggest issues was if a word was capitalised, it was considered as a named entity. Therefore in many cases, there were false positives just because there was a capital letter. In addition, certain locations were identified as a company or organisation. This is problematic too as places such as building, which often break in a disaster, would not be identified. Future research in this area would be valuable.

7.4.2 Automated image recognition

Images were found to be an important marker to identify disaster relevant tweets. However some of the tweets that had images and received high scores were not relevant for emergency services. By adding an automated image recognition algorithm it might be possible to identify if the image in a high score tweet is actually disaster relevant.

7.4.3 Keyword detection and expansion

The method of keyword detection and expansion used in this research was rudimentary. A method for expanding the list of keyword was experimented during this project and documented in Appendix F. However, the problem with word sense disambiguation existed throughout the dissertation.

Usage of undesirable keywords was extremely promising. In one dataset it managed to identify irrelevant tweets in a large quantity but in another dataset it did not have much success. However, having a curated list of undesirable keywords may be useful for other systems that attempts to identity disaster irrelevant tweets.

In addition, the list of desirable keywords can be useful for future research. By creating a list of desirable keywords based on each disaster, and loading such set of keywords in the automatic system might provide a more optimal output. Even though an attempt was made (please see Appendix G, it was not completed as it increased the scope of the research. However it showed potential and future research in this area may bring fruitful results.

7.4.4 Hashtag identification and separation

One of the most complicated challenges in Twitter is to find out which hashtag will become popular. Often it takes hours before knowing that the hashtag followed is not the dominant hashtag. One potential way to address this is by exploring contagion theory that was discussed in Chapter Two and was used to justify why retweets should be eliminated, but has broader potential.

The possible direction is to analyse prominent users' tweets and correlate multiple prominent users' hashtags to find which hashtag is getting popular. Since a prominent user is likely to know about a disaster earlier or likely to report about it earlier than others, analysing only selected users' tweet may be more useful in finding relevant hashtags than streaming all tweets from the API. Multi word hashtags such as “prayForQld” can be broken down using the vitebri algorithm to find “pray for qld”. After breaking hashtags it can then be sent to the algorithm to find if it is in potentially relevant or irrelevant tweets.

7.4.5 Better weighting

Creating a better scoring algorithm to calculate relevance score may be useful as well. Although this project has used multiple linear regression, there might be models that are a better fit. In addition to that, at present the regression coefficient was based on the multiplication of the probabilities based on one type of tweet (tweets in the damage category). Finding the probability for other types of tweets and creating an average from them may be more useful.

7.4.6 Twitter users

In this research only texts from the tweets were used to identify potentially disaster relevant tweets. Users are another important area of Twitter and research into users was not attempted in this research. However by combining the results of this research with users, such as finding how users are connected and which type of connection provides more relevant tweets, it might be possible to create an algorithm that can better identify disaster relevant tweets.

7.4.7 Different disaster dataset

Last but not least, the findings were evaluated with only two datasets. Using datasets from other disaster types such as earthquakes is likely to find if the algorithm can work across all disaster datasets or is only limited to the datasets that were tested. In addition, during this project various other types of analysis were conducted such as sentiment analysis, parts of speech analysis, and co-occurance of words analysis. The results of the analysis can be found in the Appendices G to I. As they were not fruitful they were not included in this thesis. However, they still showed promise and therefore can be investigated further.

Social media is increasingly becoming a fixture in people's lives, and the amount of information that is available after a natural disaster in social media is likely to continue to increase. The findings of this research can help in identifying actionable information from these social media streams to assist emergency services organisations to better target resources, improve response times, and hopefully reduce the number of causalities.

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Appendices

Appendix A: Sample Json file

Sample JSON file for twitter entities

{
   "id": 411031503817039874,
   "id_str": "411031503817039874",
   "text": "test $TWTR @twitterapi #hashtag http://t.co/p5dOtmnZyu https:
//t.co//ZSvIEMOPb8",
   "created_at": "Thu Dec 12 07:15:21 +0000 2013",
   "entities": {
      "hashtags": [{
         "text": "hashtag",
         "indices": [23, 31]
      }],
      "symbols": [{
         "text": "TWTR",
         "indices": [5, 10]
      }],
      "urls": [{
         "url": "http://t.co/p5dOtmnZyu",
         "expanded_url": "http://dev.twitter.com",
         "display_url": "dev.twitter.com",
         "indices": [32, 54]
      }, {
         "url": "https://t.co/ZSvIEMOPb8",
         "expanded_url":
"https://ton.twitter.com/1.1/ton/data/dm/411031503817039874411031503833792512cOkcq9FS.jpg",
         "display_url": "pic.twitter.com/ZSvIEMOPb8",
         "indices": [55, 78]
      }],
      "user_mentions": [{
         "screen_name": "twitterapi",
         "name": "Twitter API",
         "id": 6253282,
         "id_str": "6253282",
         "indices": [11, 22]
      }],
      "media": [{
         "id": 411031503833792512,
         "id_str": "411031503833792512",
         "indices": [55, 78],

"media_url":
"https://ton.twitter.com/1.1/ton/data/dm/411031503817039874411031503833792512cOkcq9FS.jpg",
"media_url_https":
"https://ton.twitter.com/1.1/ton/data/dm/411031503817039874411031503833792512cOkcq9FS.jpg",
"url": "https://t.co/ZSvIEMOPb8",
"display_url": "pic.twitter.com/ZSvIEMOPb8",
"expanded_url":
"https://ton.twitter.com/1.1/ton/data/dm/411031503817039874411031503833792512cOkcq9FS.jpg",
"type": "photo",
"sizes": {
"medium": {
"w": 600,
"h": 450,
"resize": "fit"
},
"large": {
"w": 1024,
"h": 768,
"resize": "fit"
},
"thumb": {
"w": 150,
"h": 150,
"resize": "crop"
},
"small": {
"w": 340,
"h": 255,
"resize": "fit"
}
}
}]
}
...
}

Appendix B: Data Collection Process

The setup process of yTK involves setting up a computer as a web server and then install the program into the web server. The details of the system architecture as well as the setup process can be found in this URL:

http://jobrieniii.tumblr.com/post/15240403050/how-to-install-yourtwapperkeeper-on-a-rackspace-cloud .

Once it is installed, a list of twitter accounts that is allowed to enter tracking keywords or hashtags are included into the system. After that it needs to be authorised from an existing twitter account before someone wants to track a particular keyword.

Collection process: The data collection process with yTK involves manually entering the hashtag or the keyword into yTK. The process to do is to open that URL of yTK with browser, authenticate with Twitter account and then enter the keyword that needs to be tracked (Figure 53).

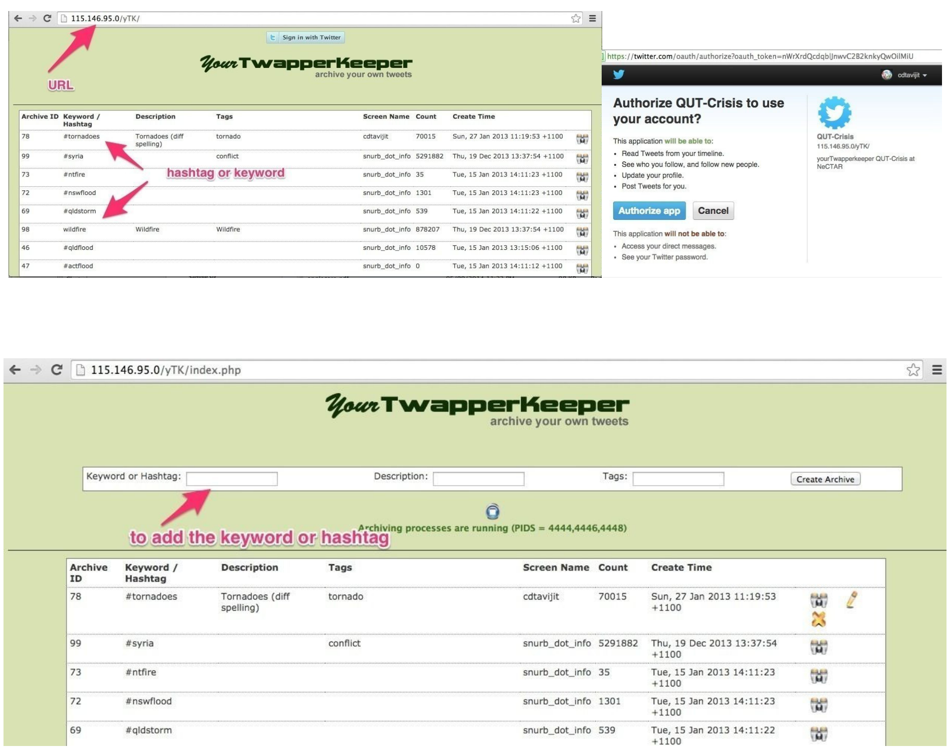

Figure 53: yTK initial screen and archiving steps

Appendix C: Setting up development platform

The development platform consists of database and the programming environment.

Database Setup

MySQL database was used for this project as it is an open source database platform. To integrate SQL development, administration and design MySQL workbench was used as an integrated development environment. Both MySQL and the workbench is downloadable from their respective website for free. For this project, MySQL was downloaded along with the server under XAMPP package. Once the database was installed, entire Yolanda dataset was inserted in the database. All related Sql scripts are included in appendix D.

Server setup

Although this project did not involve real-time data integration from twitter, to enable web-based output, Apache server was installed. Both the server and the database was downloaded from XAMPP website.

Importing and making connections

Once the setup was completed, a new database was created in the MySQL database. In that database, a new tabled called typhoon was created and was populated with the yolanda dataset. The script to create the table and importing csv file is available in another Appendix.

Programming environment setup

Various research has used Python (Aggarwal, 2011; Helbing & Balietti, 2011; Lavalle, et al., 2011) and awk (Bruns, 2011) to analyse Twitter data. However as natural language processing was used in this phase Python was the preferred choice due to its popularity as data mining language as well as existing libraries that deals with natural language. Once Python is downloaded and integrated with the database, required packages were downloaded. The list of the packages and the reason for choosing them is outlines in Table 30.

Name	**Version**	**Description**
Python	2.7.6	Although this is not the latest version, this is the most compatible version that works with all the packages.
MySQL-	1.2.5	It is extremely important to install the correct version because failure

Python		to do so results in various problems. It is recommended that MySQL is installed with an EXE file for windows or via macport in mac. Alternatively it could also be installed using MySQL python connector.
nltk	2.0.4	This is the latest version of Natural Language Toolkit. Once installed, all the related components such as “english stop words” needs to be downloaded via nltk as well.
stemming	1.0	To remove plural, adjective, adverb etc in order to only export the basic word.
twython	3.1.2	To connect and find additional information on twitter
virtualenv	1.11.4	Virtual environment allows creating an isolated working copy of Python with specific versions so that it can be distributed and installed in another machine correctly.
wikipedia	1.1	To search for Wikipedia entries related to a specific keyword

Table 30: List of python packages used in this project.

IDE setup

Although setting up an integrated development editor is not an essential component of the project, it is extremely useful to set up an IDE that works well with the programming environment. For the purpose of this project, an IDE named “Sublime text” was used due to it’s support of various file types and speed of working with large file sizes.

Appendix D: SQL Queries & Python Scripts

All available scripts related are hosted in Github as an open source project. Please visit https://github.com/cdtavijit/krisisdetect for the source codes.

In general the source code includes

1. MySQL scripts
2. Python scripts that uses

a) URL resolve

b) Image detect from a wikipedia list

c) Named entity script that connects with stanford named entity list

d) Other related script.

Appendix E: List of Keywords

This is the list of keywords that requires curation in the future as different crisis and different system emerges.

Coding Categories	#qldfloods Keywords	Yolanda Keywords
Request for material support (RF, RS)	Seeking, help, flood, animals, roof	Also, any, badly, bodies, candles, damaged, dead, dire, electricity, everything, flashlight, food, from, goods, haven't, help, isolated, need, no, out, please, pls, received, relief, rescue, running, School, send, signal, update, water
Request for medical assistance (RM)	None available	Please, need, medicines
Request for information (RP, RA, RI)	Anyone, contact, current, have, know, mum, old, power, safe, situation	Any, anyone, anything, boyfriend, bring, check, colleague, contact, families, family, father, find, finding, for, friend, help, husband, knows, looking, lost, mother, out, people, plz, relatives, relief, rescue, son, still, update, yet
Request for other types of help (RH)	animal, anyone, can, dog, evacuate, looking, offer, organise	Please, send, relief, goods, dire, need, asking, help
Report of damage (DP, DH, DE, DC, DI)	50 cm, across, another, area, at, basement, been, braces, bridge, brim, closed, closes, Coming, corner, crocodile, debris, destroyed, direction, door, down, ferry, filling, flash, flat, floating, flood, floodbound, flooded, flooding , flow, from, full, getting, gone, good, height, high, higher, hour, house, indistinguishable, lake, large, later, line, low, massive, meant, midday, near, nearly, next, no , now, on, our, out , peak, quickly, raw, rising, river, riverside, roads, rise, scene, second, serene, sewage, someone, soon, spewing, still, street, surging, swallowed, terminal, tide, time,	after, almost, badly, blackout, bldg, block, bridge, cables, casualties, city, communication, damaged, destroyed, detach, disconnects, down, electrical, electricity, failed, fallen, falling, giant, help, hit, hitting, houses, impassable, knocks, leaning, lines, lost, need, number, outage, please, power, roads, roof, storm, strong, supply, their, trees, winds

	towers, under, underwater, Water, waterfront, were, worst	
Reporting community behaviour (CB, CC)	creeping, donate, evacuating, fever, flood, grim, helpless, homes, information, located, looting, lost, morgues, near, polluted, power, river, safe, sandbag, shot, submerged, temporary, washes, water, wrong	200, electricity, evacuating, evacuation, evacuees, families, forced, municipalities, out, residents, waters
Reaction from community (RE, RC)	amazing, anyone, asking, avoid, back, call, charger, check, donate, donated, extraordinary, floodwater, follow, great, help, list, needs, offer, out, pack, people, phenomenal, photo, picture, please, proud, really, safe, session, suffering, superb, together, try, volunteer, when	badly, haven't, help, need, now, please, reaching, received, send, yet
Others (OM, OS, OG, ON, OR)	According, business, buy, comparisons, ideological, God, lord, love, mercy, miracle, pray, prayer, price, purchase, sexy	analyst, article, beautiful, believe, bless, breaking, calm, charts, discussion, glad, God , heart, hell, heroes, jobs, lord, love, mercy, mighty, miracle, pray, prayer, psalm,report, sex

Table 31: Common keywords in qldfloods and Yolanda dataset based on their coding categories

Appendix F: Extending with Wikipedia & Wordnet

Expansion of the keywords often falls under query expansion strategy (Anagnostopoulos, et al., 2012; Lau, et al., 2011). This is generally conducted using various methods that include searching for synonym via designated lexical database, looking for other Lexemes or word forms, fixing spelling mistakes (such as pls to please). This section describes the method and findings related to this .

Using Wordnet to find Synonym

In order to expand the queries, it is a common practice to use wordnet (Banerjee & Pedersen, 2002; Montejo-Ráez, Martínez-Cámara, Martín-Valdivia, & Ureña-López, 2014) as it hosts the synonyms based on their "senses" or "Lexemes". For example, if the word "brother" is searched through wordnet, it returns the following "senses" - blood brother, buddy, chum, crony, pal, sidekick, comrade. As it can be seen from the example, all the senses carry different meaning. Among these senses, even though "blood brother" is potentially what people would look for in the tweet, it is unlikely to type "blood brother" in the tweet. Similarly, they are not likely to write about their "chum". However, it is possible that they may look for their "pal" or "buddy" which are common language to look for friend. Therefore usage of Wordnet still remains relevant.

Using wikipedia to find related keywords

Using wikipedia categories on the other hand has not been used often in disaster context. However when the same word "brother" is searched through wikipedia an interesting observation can be made. According to the wikipedia template, "brother" is grouped under "Family" which also lists related words such as "sister", "son", "daughter" etc. Therefore by looking for words that belongs to the same group, it is possible to expand the list of keywords better than wordnet. Figure 54 demonstrates an example wikipedia template category (often located at the bottom of the page) which lists all possibly related words that wikipedia contributors though is related to the word Roof.

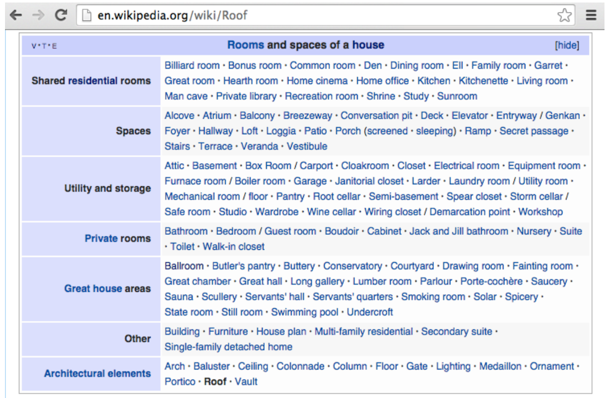

Figure 54 : Wikipedia group for the word roof

Comparing wikipedia and wordnet

Table 32 lists the keywords that can be identified through both wordnet and wikipedia based on the two words “brother” and “roof”. From the table it can be seen that even though wikipedia categories are not synonyms, they belong to the same group that is likely to be searched for. For example, when someone tweets about roof blowing away, someone else might talk about bedroom getting flooded. Instead of looking for exact synonyms through Wordnet or other lexical categories, identifying which group the word belongs to and finding other words from the same group is likely to generate better filtered tweet.

extraction method	Brother	Roof
Wikipedia	Spouse, Husband, Wife, Parents, Father, Mother, Children, Son, Daughter, Siblings, Sister, Uncle, Aunt, Nephew, Niece, Grandchildren, Grandson, Granddaughter, Grandparents, Grandfather, Grandmother, Great-grandchildren, Great-grandson, Great-granddaughter, Great-grandparents, Great-grandfather, Great-grandmother, Great-uncles, Granduncle, Grandaunt,	Arch, Baluster, Ceiling, Colonnade, Column, Floor, Gate, Lighting, Medaillon, Ornament, Portico, Vault, Ballroom, Buttery, Conservatory, Courtyard, Drawing room, Lumber, Parlour, Saucery, Sauna, Scullery, Servant room, Smoking room, Solar room, Spicery, State, Swimming pool, Undercroft, Bathroom, Bedroom, Boudoir, Cabinet, Jack, Nursery, Suite, Toilet, Attic, Basement, Box, Cloakroom, Closet, Electrical, Equipment, Furnace, Garage, Janitorial, Larder, Laundry, Mechanical, Pantry, Root, Semi-basement, Spear, Storm, Studio, Wardrobe, Wine, Wiring, Workshop, Alcove, Atrium, Balcony, Breezeway, Conversation, Deck, Elevator, Entryway, Foyer, Hallway, Loft, Loggia, Patio,

	Great-nephews, Grandnephew, Grandniece, Cousin, Parents-in-law, Mother-in-law, Father-in-law, Sister-in-law, Brother-in-law, Siblings-in-law, Son-in-law, Daughter-in-law, Children-in-law	Porch , screened, sleeping, Ramp, Secret, Stairs, Terrace, Veranda, Vestibule, Billiard, Bonus, Common, Den, Dining, Ell, Family, Garret, Great, Hearth, Home, Kitchen, Kitchenette, Living, Man, Private, Recreation, Shrine, Study, Sunroom
Wordnet	brother, blood brother, buddy, chum, crony, pal, sidekick, comrade	ceiling, cap

Table 32: Related keywords based on two given keywords

Findings with expanded queries

As it can be seen from Figure 55, inclusion of expanded queries resulted in improved performances. On top of 4 entries under request for help category with the brother keyword (Fig 67), wikipedia entries registered additional 122 entries. By evaluating further it reveals that it indeed finds crucial tweets such as "@ANCALERTS #RescuePH My grandparents need an urgent help, thou we do not have any connections with them yet. (cont) http://t.co/9DZaYaHS0h:" or "Looking to help a friend find news of her husband working in the Ormoc area of Leyte.If anyone knows anything.Please let me know #YolandaPH". Although tweets under not related category still remains the biggest category, findings from this expansion finds lot more important tweets. Words from the Worndet category however did not find any important tweet as expected.

Tweets related to damage also added another 286 tweets that had other words found from wikipedia category for the word "roof". And these tweets were genuinely important for emergency services. For example, "AKLAN: Kalibo Airport still closed, damaged roofs. Fair weather. Uprooted trees and posts on highways. #YolandaPH @philredcross" or "No water or electric supply in #Bohol Most of affected municipalities are Alicia, Buenavista, Carmen, and Trinidad #Haiyan @SC_Humanitarian" had genuine reports of the situation. Word from the Wordnet category also resulted in tweets about a ceiling collapse - "UP Town Center ceiling collapses, injures 3 http://t.co/e95cHeTOdh #YolandaPH"; which also suggests useful tweet.

However, the biggest issue remained is the large section of unimportant tweets. Once these tweets were evaluated it can be seen that, a large section of the tweets also contains unimportant words. For example, tweets with “brother” also had keyword from the unimportant category list, such as “All my prayers to our brothers and sisters that our affected by Yolanda there in Tacloban. Keep safe! #PrayForThePhilippines #YolandaPH”. On top of having country level name of the place, it is the spiritual word in the tweet that makes it unimportant for emergency services.

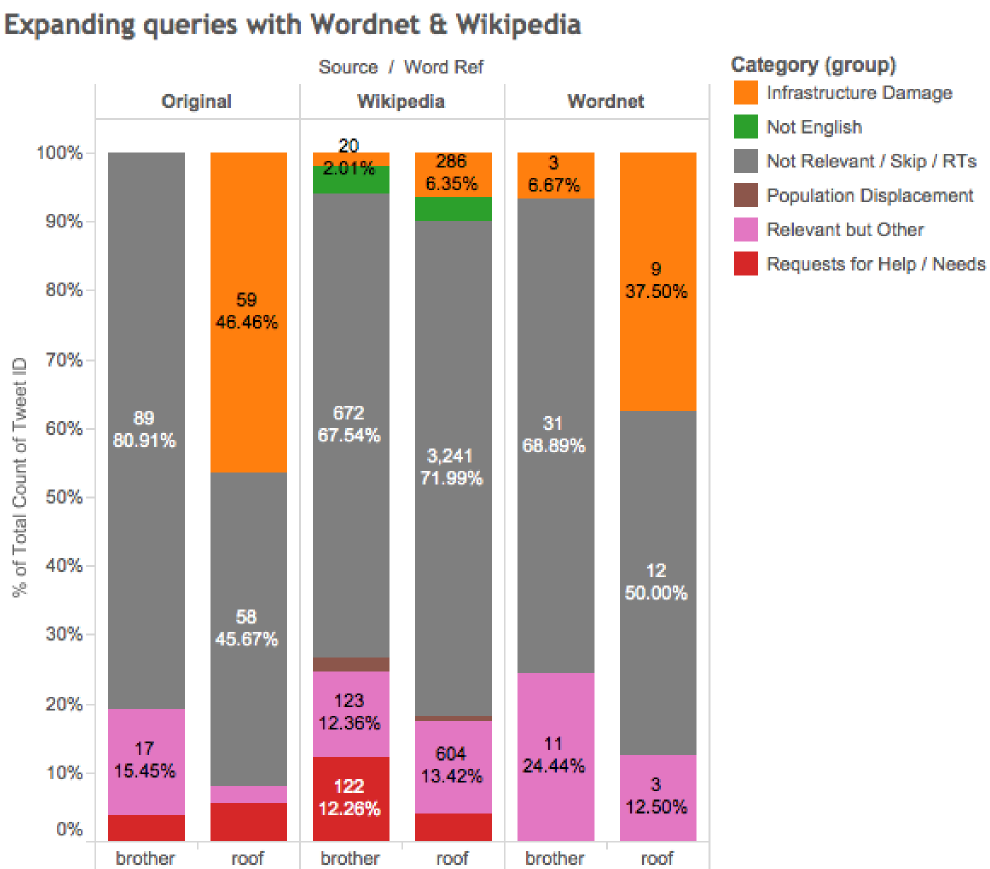

Figure 55 : Expanding query for two keywords

Similar patterns was seen in the extended queries as well. For example, “Praying my little cousin stays she and away from be typhoon hitting the #philippines #PrayForThePhilippines #family”, and “Abba Father, embrace our dear land, the Philippines. May your love, grace, mercy and compassion be upon Your people. #Haiyan #YolandaPH” both were found in the Fig 62 result and fell under “not relevant” category and both had words that was in the negative list.

With regards to the expanded search that used groups related to “roof” also had similar pattern. For example, one of the related word was “home”, which resulted in tweets such as “Reporters are always braving the elements in the line of duty. Bravo to all of you.May God bring you home safely to your families.#YolandaPH”. Once again, it had the word “God” from the unimportant keyword list.

As including the expansion list increases the scope of the project, it was not executed further but it suggests that including wikipedia and wordnet can be a viable keyword list extension tool.

Appendix G: Using Co-occurance of keywords

One of the way to address the issue that occurs with single keyword is to use co-occurence of keywords (Matsuo & Ishizuka, 2004; Schatz, Johnson, Cochrane, & Chen, 1996). For example, “please help” is extremely different than “please RT” because in one tweet someone might be asking for help and therefore important for emergency services but in another tweet they are asking to promote an existing tweet and is not important for emergency services.

Stop words removal

However, there are additional issues when co-occurance is extracted from twitter using an automated system. The first problem is conjunctions such as “and”. For example, if a tweet is asking for food and water, and co-occured words with “food” is search, it will generate “food and” as the answer. However in this case, identifying “food water” will be more meaningful as that will have stronger indication of importance. Therefore by removing all Stop words based on NLTK database, tweets were processed to identify which keywords are associated with the words “help” and “please”.

Removal of stop words is a commonly used practice in natural language processing and is commonly used in search engines to identify key words people are asking (Manning & Schütze, 1999). Although various research has used different variety of n-grams (n number of words) to identify co-occurred words in discovering topics with natural language processing, for this part bi-grams were used to find out which two words are often-assocaited in the important tweets.

Introducing Stemming

Once again, all the words were stemmed to ensure they match the root form in order to eliminate variations. Therefore, helped, helping, help will all be counted as one instead of three separate words.

From the list of co-occurred words in Fig 68 (sorted based on request for help category after stop words were eliminated and words were reduced to their basic form), it can be seen that “please help” was the highest co-occurred words that included either “please” or “help”. Although “help victim” was the second most co-occurred keyword pair, it also appeared highly in the “not relevant” category. Similarly, “help typhoon” and “help Philippines” was high in both lists. Further analysis reveals that this is due to many tweets that were asking for generic help who may not actually be in the affected area.

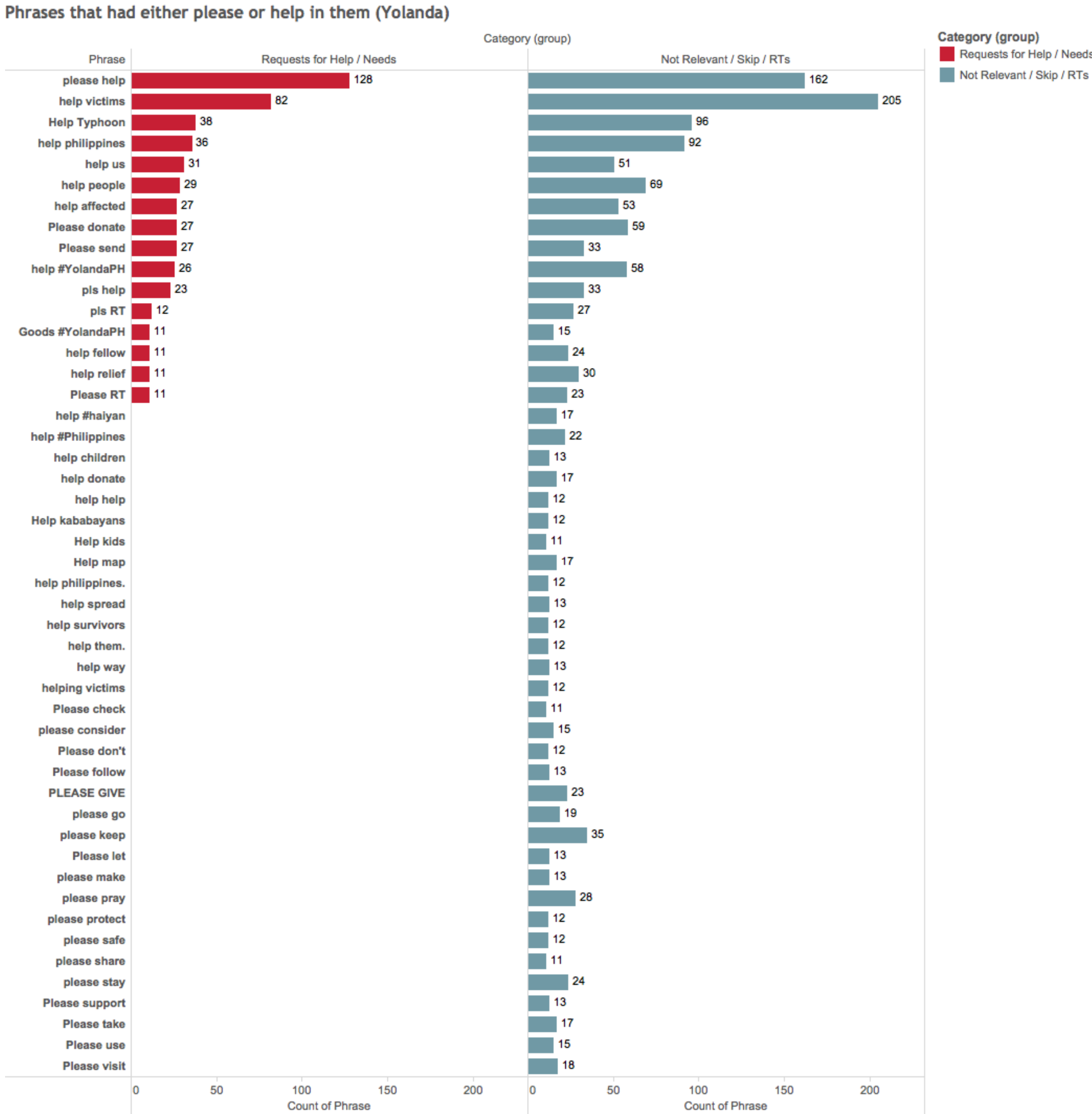

Figure 56 : Presence of same word across multiple categories

When the list of keyword is expanded beyond the top keywords to something more important, such as food, the results were similar (Fig 69 with limiting data to at least 4 occurrence). Top co-occurred words "food" & "water" were present in both important and not important categories. However, when the tweets were evaluated, the contents showed a clear difference of why one of the tweet was inside important category and why the other was not. For example, "Bogo City, Cebu is also in dire need of food and water. Dinadaan-daanan lang. They haven't received any relief goods yet. #ReliefPH #kristv” was in the in the Request for help category but “Concerns Grow Over Pace of Aid to #Philippines, situation grows more desperate, supplies food & water running low http://t.co/WL2jrWkvIe” was rightly in the not relevant category as it was merely pointing to the New York times report.

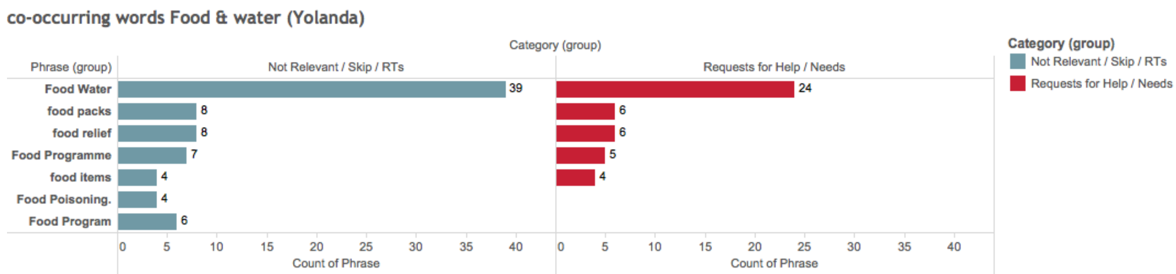

Figure 57 : Presence of food & water across two categories

Again, the results in Figure 56 and Figure 57 reflects the same findings as other keyword related findings that it is extremely difficult to identify important tweet based on the keyword alone. Therefore the next section looks at part of speech to find out if finding part of speech will be able to determine is the tweet was important or not.

Appendix H: Using Sentiment Analysis

Although sentiment analysis was not addressed in the Phase 1, it is often a feature used by various twitter researchers. Therefore it was tested to see if this can identify important tweets. Two sentiment analysis module was used for this test. One is "Pattern Analyzer" based on Pattern library (De Smedt & Daelemans, 2012) and the other is "Naive Bayes Analyzer" which was trained using NLTK movie corpus review.

Pattern Analyzer

Pattern has been used for opinion mining and sentiment analysis in various projects, notably to analyse tweets in Belgian elections in 2010. By calculating sentiment analysis of each word and then combining the scores of tweet it delivers a score ranging from −1 (negative) to +1 (positive). For analysing sentiment of Yolanda tweets, pattern library was used for the entire dataset and which resulted in a score that ranged from the positive to negative.

Naive Bayes Analyzer

The default training set Naive Bayes Analyzer that was used for this test was trained with a movie review dataset. Although for In an ideal situation a Naive Bayes classifier should be trained using dataset that is suitable for the task, it has been reported to perform well for other situations as well (Weichselbraun, Gindl, & Scharl, 2013; Xia, Zong, & Li, 2011). Therefore the default option was used to test how well it performs.

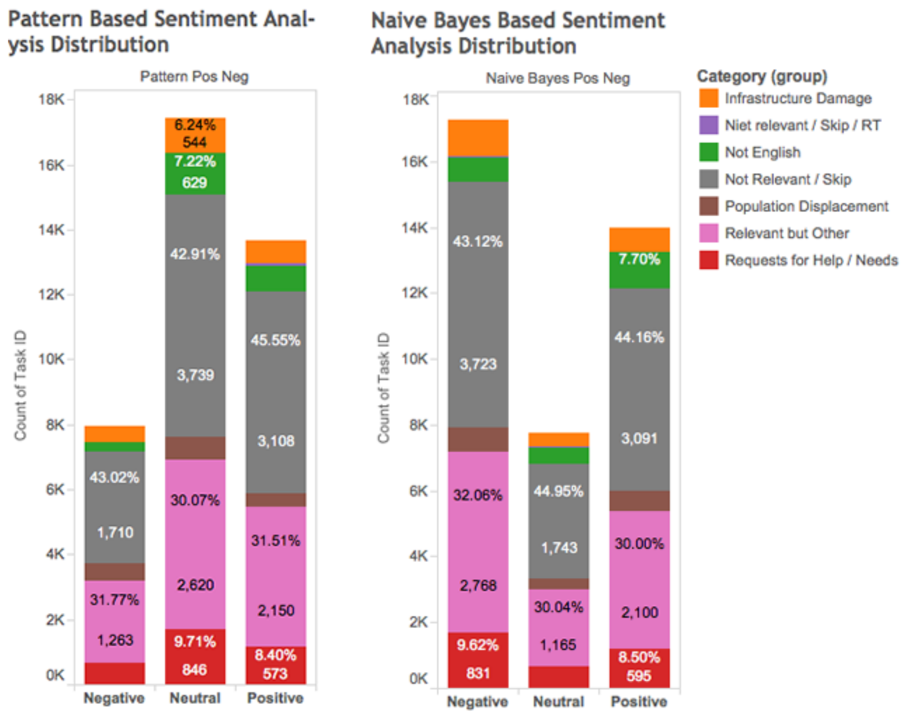

Figure 58 : Overall Findings from sentiment analysis using Pattern and Naive Bayes Analyzer

As it can be seen from Figure 58, the results are anything but consistent. From the pattern based sentiment analysis most of the tweets were classified as neutral. On top of that there were more positive sentiment then negative sentiment. Naive Bayes analyses rather performed better as it can be seen from the figure. However as the focus is to understand if these can be used to determine important tweets, the three important categories were separated (Figure 59).

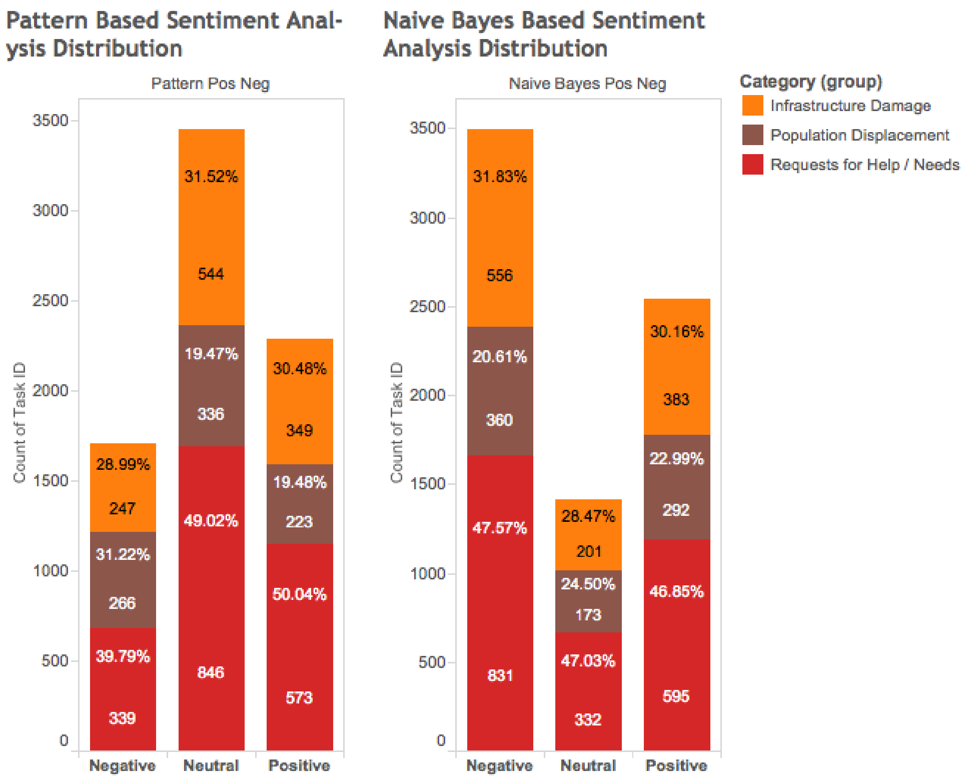

Figure 59 : Sentiment analysis using Pattern and Naive Bayes Analyzer on tweets from 3 categories

According to both pattern and naive bayes analysis, categories under infrastructure damage, request for help or population displacement has a large percentage of positive as well as neutral sentiments. For example, “Roofs flying, trees uprooted, fallen at 6am. Catastrophic is an understatement for #YolandaPH #Haiyan #PHSaveChildren #SC_Humanitarian” was classified under “neutral” with pattern analyser (score of 0.00) although this is definitely an important tweet.

Similar to that, “Oh no! Hope everyone in the #Philippines is OK! Super typhoon Haiyan just broke all scientific intensity scales http://t.co/hx5nKZuxgz” have been classified as negative with the naive bayes, “No electricity now here at Gandara Samar so dark outside and only the strong wind and rains can be heard plus the frogs kokak @philredcross” was identified as positive.

Based on the results it can be suggested that sentiment analysis, at least with the default options is unable to identify important tweets, rather using sentiment analysis for disaster tweet is likely to to create more noise. Although training Naive Bayes dataset with specific disaster related tweet may be able to identify important tweets, this was beyond the scope of the research and therefore was not conducted.

Appendix I: Using part of speech

Phase 1 results also indicates that certain parts of speech such as verb, adjective, adverb are usually more prominent in important categories. In addition to that, Part of speech has been used by various research to analyse crisis related twitter dataset (Corvey, et al., 2010; Imran, et al., 2013b; Panem, et al., 2014; Verma, et al., 2011) as well. However each research project have focused on various part of speech. Some have focused on verb, while some other looked at personal pronoun, adverb, determiner.

Since the data set used in this research was pre-evaluated, part of speech detection algorithm was applied on each tweet to see if there is any specific pattern in the tweets. For example, if the tweets with infrastructure damage has more verb, then verb should be looked for in the tweet. And for the purpose of this research, Carnegie Mellon Ark-Tweet-NLP (Chris & Schneider, 2012) was used. Similar to named entity, there are various competing part of speech tagger available. Among them, notables ones are : Stanford Named Entity recognition (Finkel, et al., 2005) , University of Washington Twitter NLP Tools (Ritter, et al., 2011) and Carnegie Mellon Ark-Tweet-NLP (Chris & Schneider, 2012).

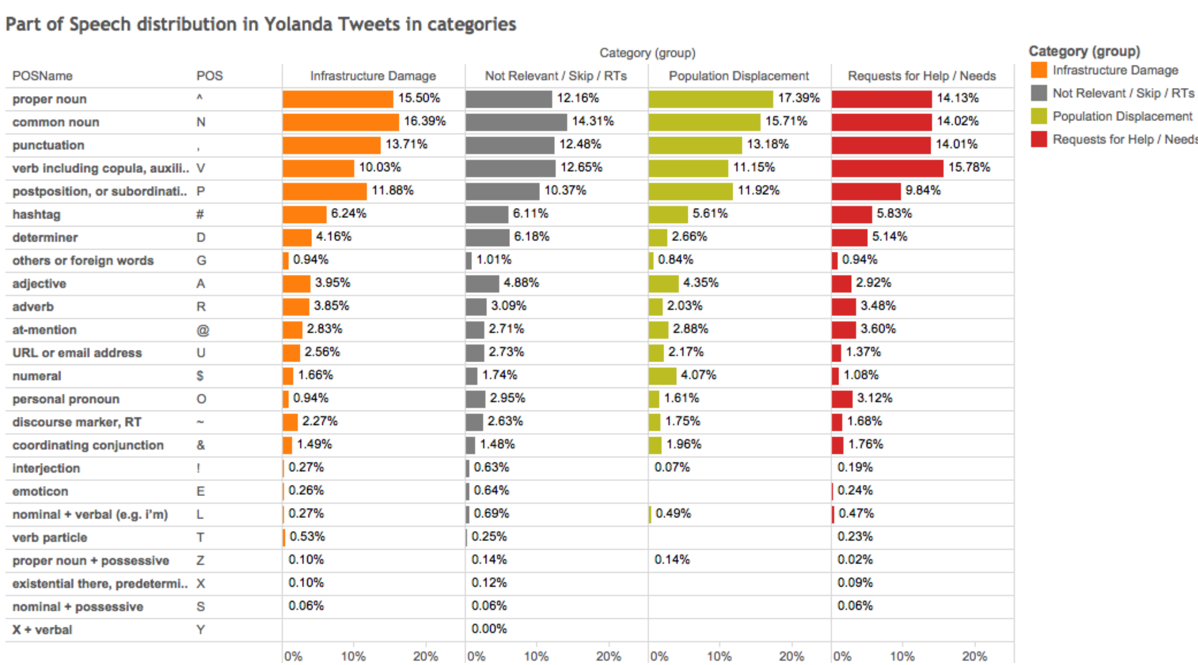

Figure 60 : Overall distribution of Part of Speech in Yolanda tweets from 4 categories

Based on that analyses in Figure 60, it can be seen that as a single feature part of speech is also unable to determine important tweet. However there is indeed more percentage of verb in the request for help on needs category compared to other categories.

In Phase 1, addressing to a prominent user was found to be a marker of importance. However, Figure 61 suggests that, that itself is not a good indication as well because a large number of not related tweets were addressed to someone else as well. Position of hashtag was tested as well and based on the result it can be seen that, hashtag positions were also unable to provide a conclusive answer.

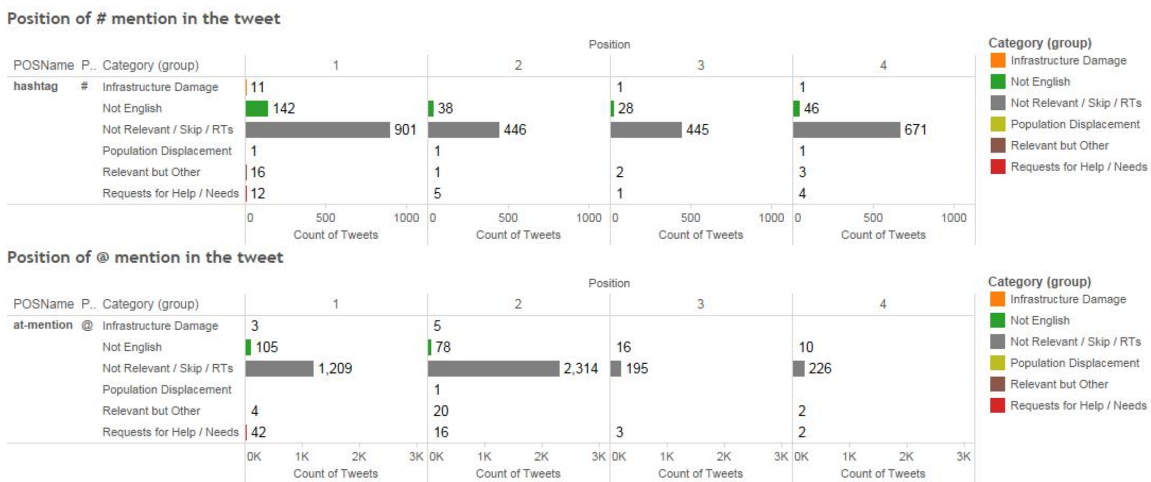

Figure 61 : Position of at mention and hashtag in different categories.